# Automatic Summarization (and other stuff)


Taylor Berg-Kirkpatrick
CS 288 UC Berkeley


# Summarization

Berkeley NLP

# Summarization

Berkeley NLP

# Multidocument Summarization



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# Sentence Extraction




Lindsay Lohan pleaded not guilty Wednesday to felony grand theft of a 2,500 necklace, a case that could return the troubled starlet to jail rather than the big screen.

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The Mean Girls star is due back in court on Feb. 23 an important hearing in which Lohan could opt to end the case early.


# Maximum Marginal Relevance

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N L P

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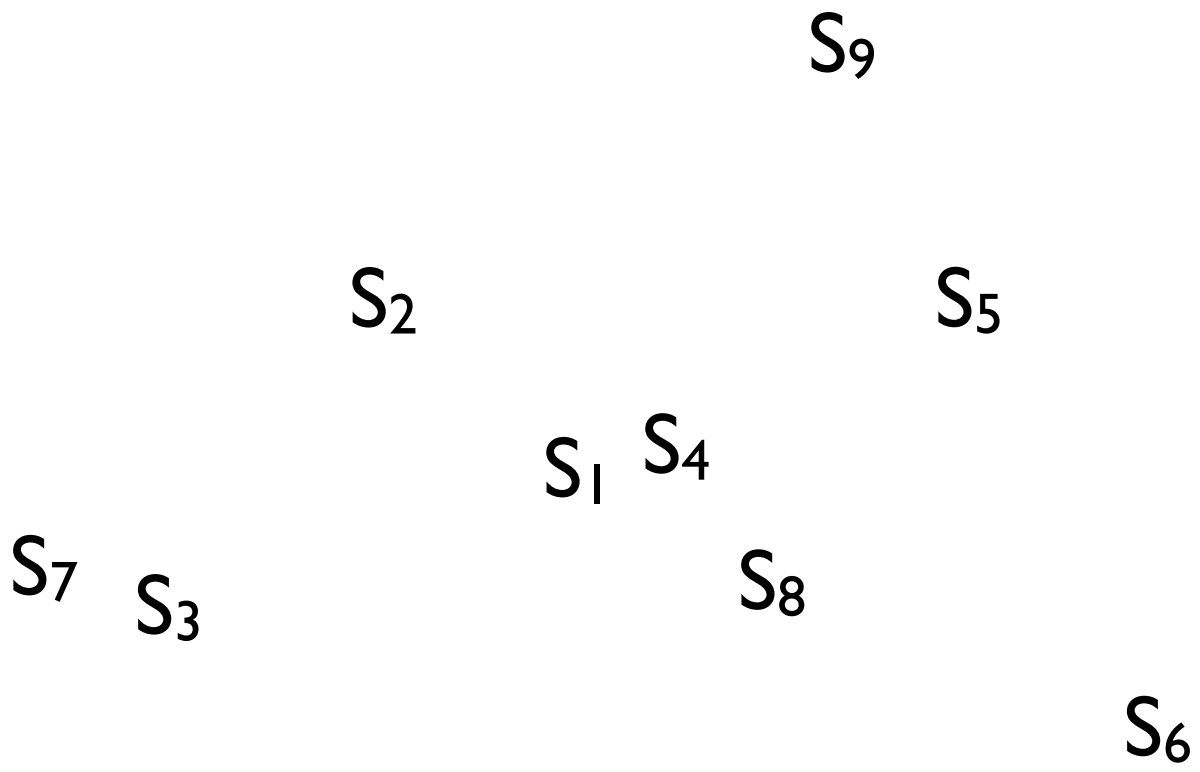

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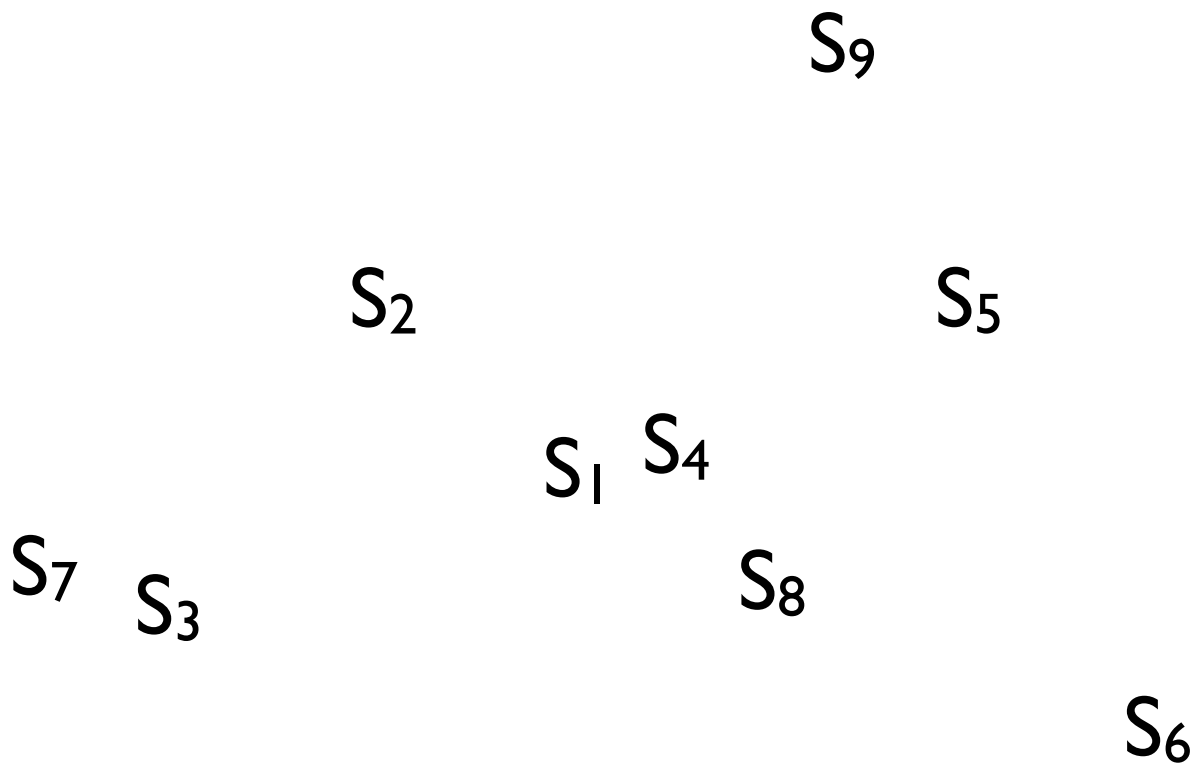

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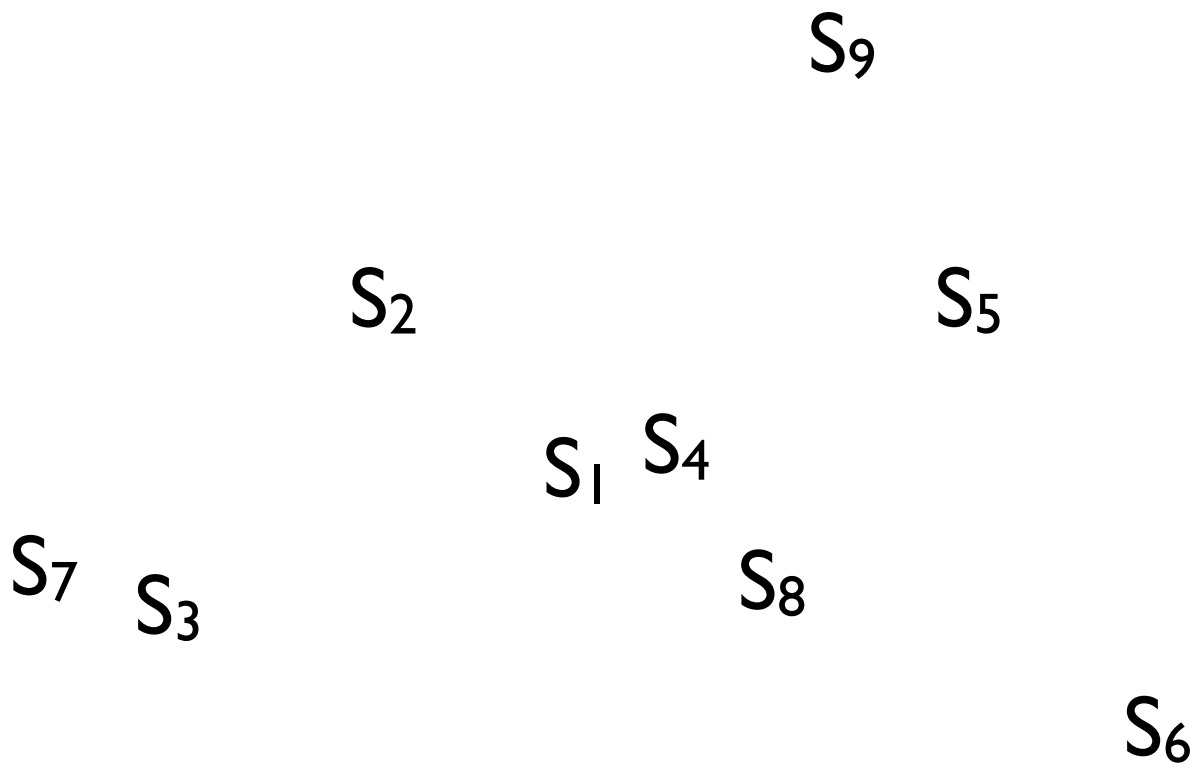


$S_1$: She traveled to France on Friday.

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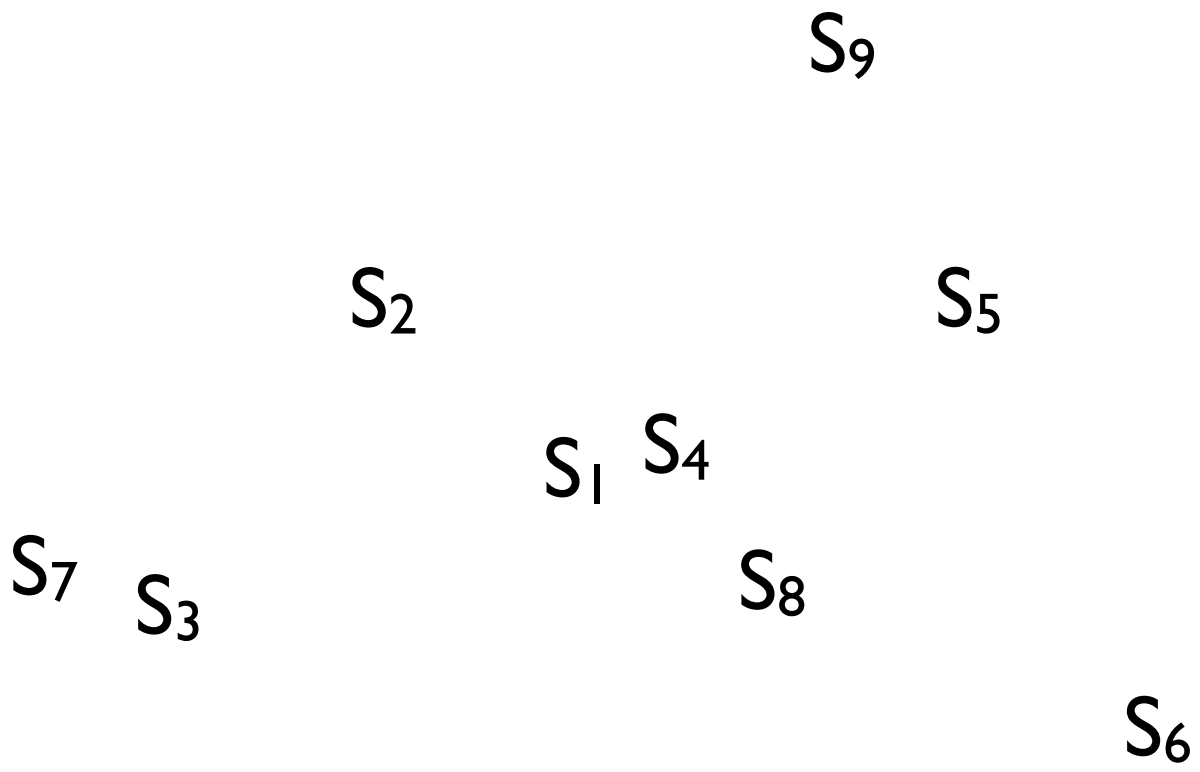


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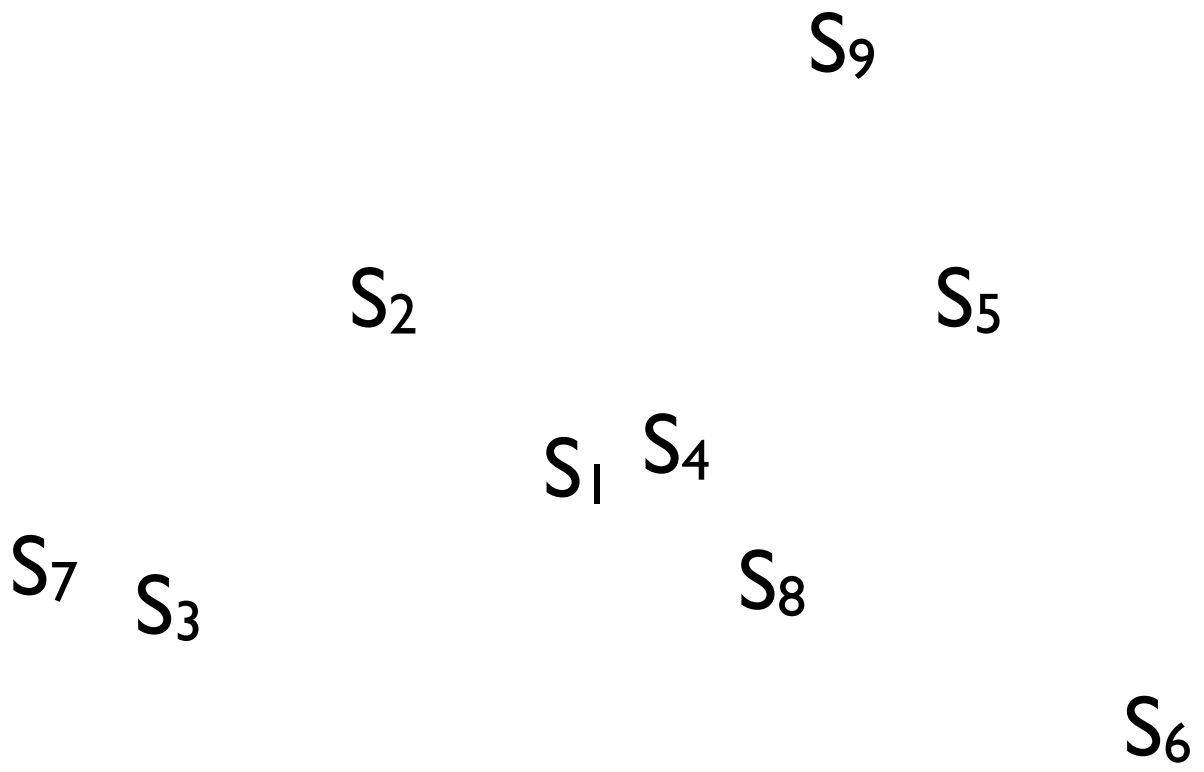


S1: She traveled to France on Friday.

S4: On Friday, She took a trip to France.

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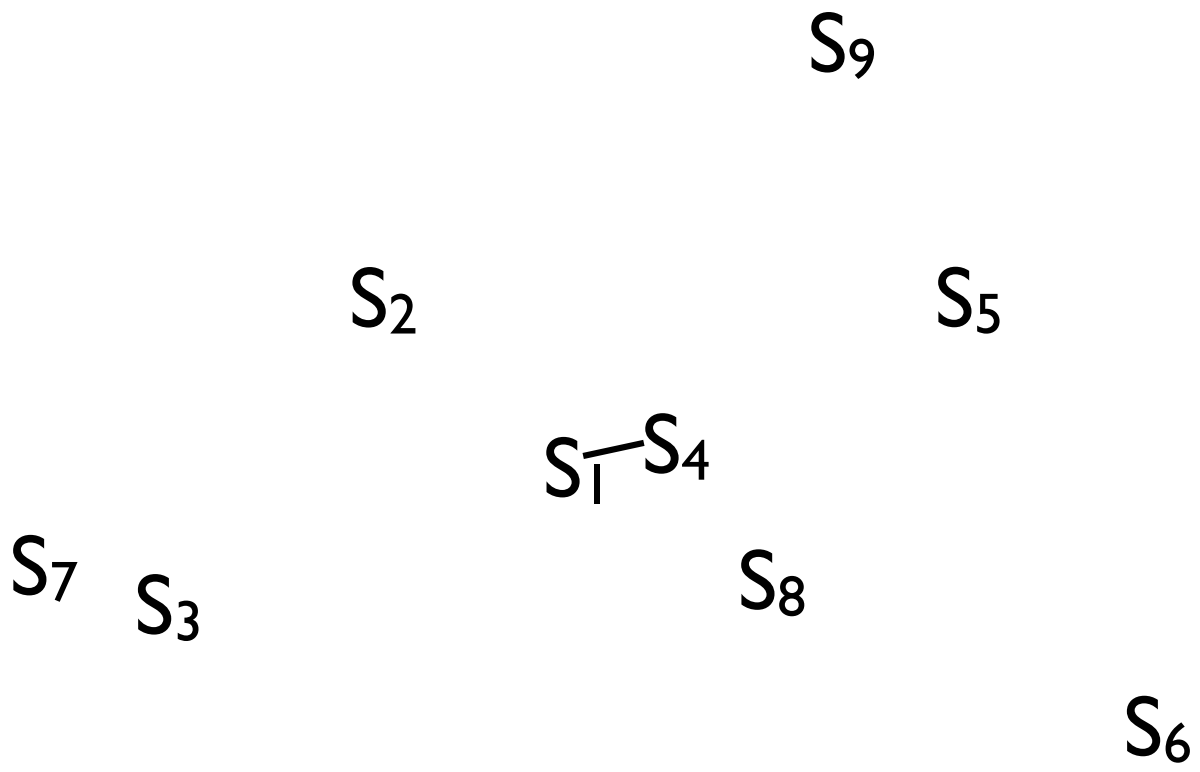


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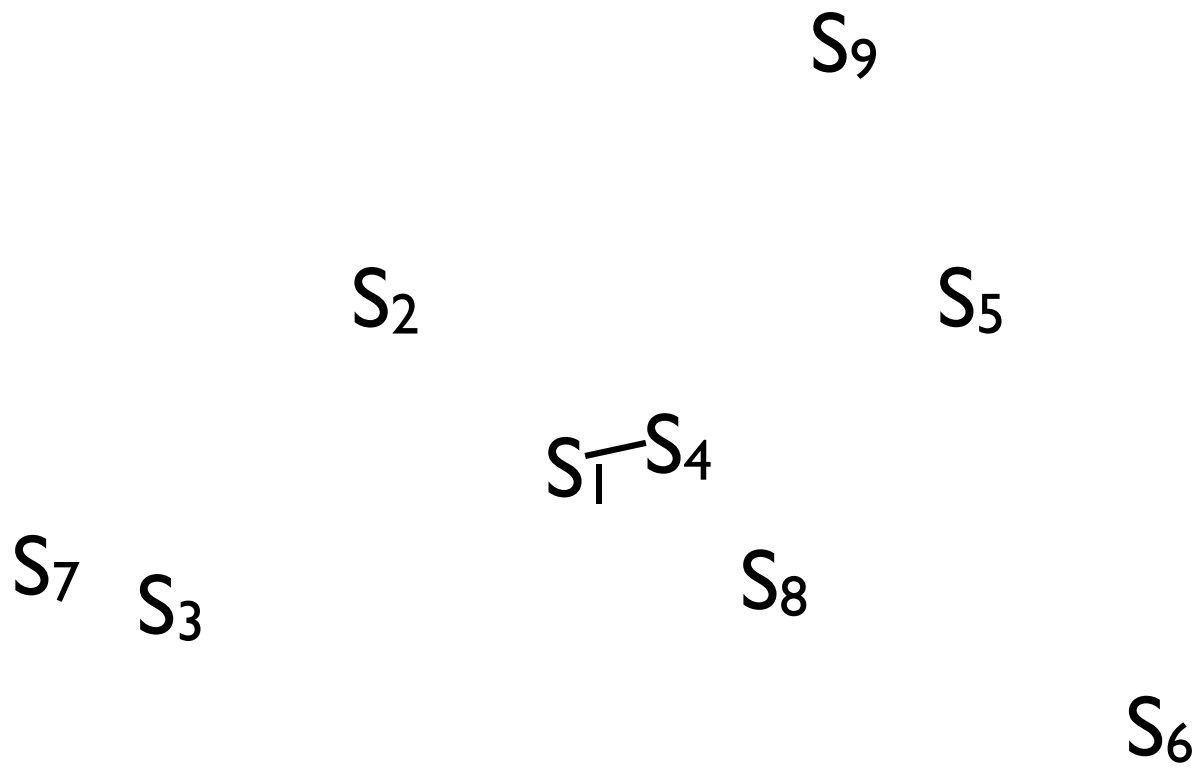


$S_1$: She traveled to France on Friday.

$S_4$: On Friday, She took a trip to France.

$S_8$: She plans to stay for two weeks.

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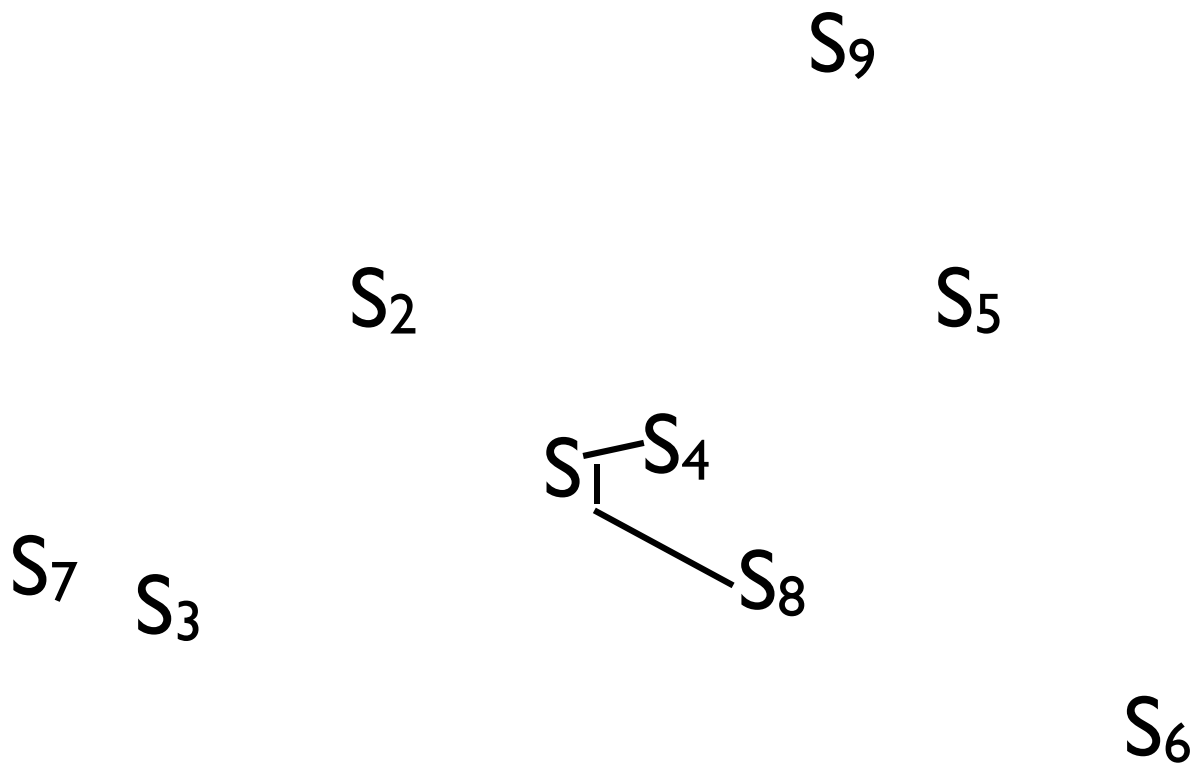


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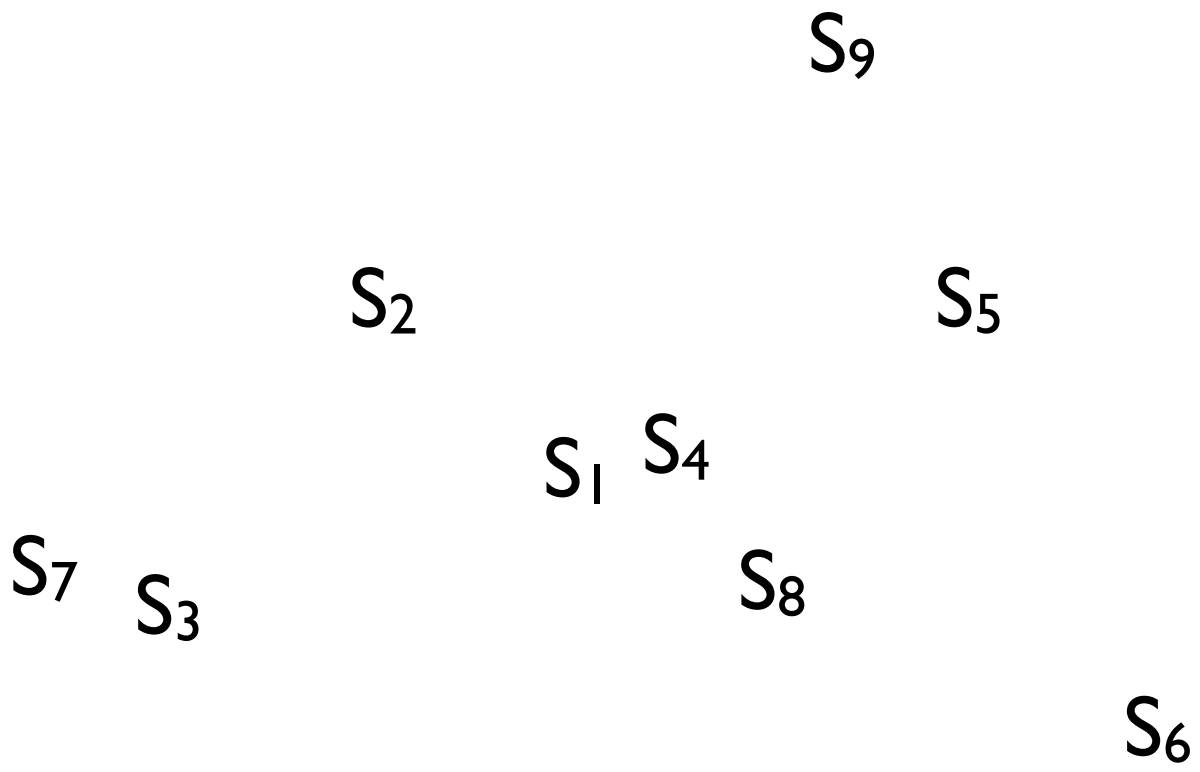

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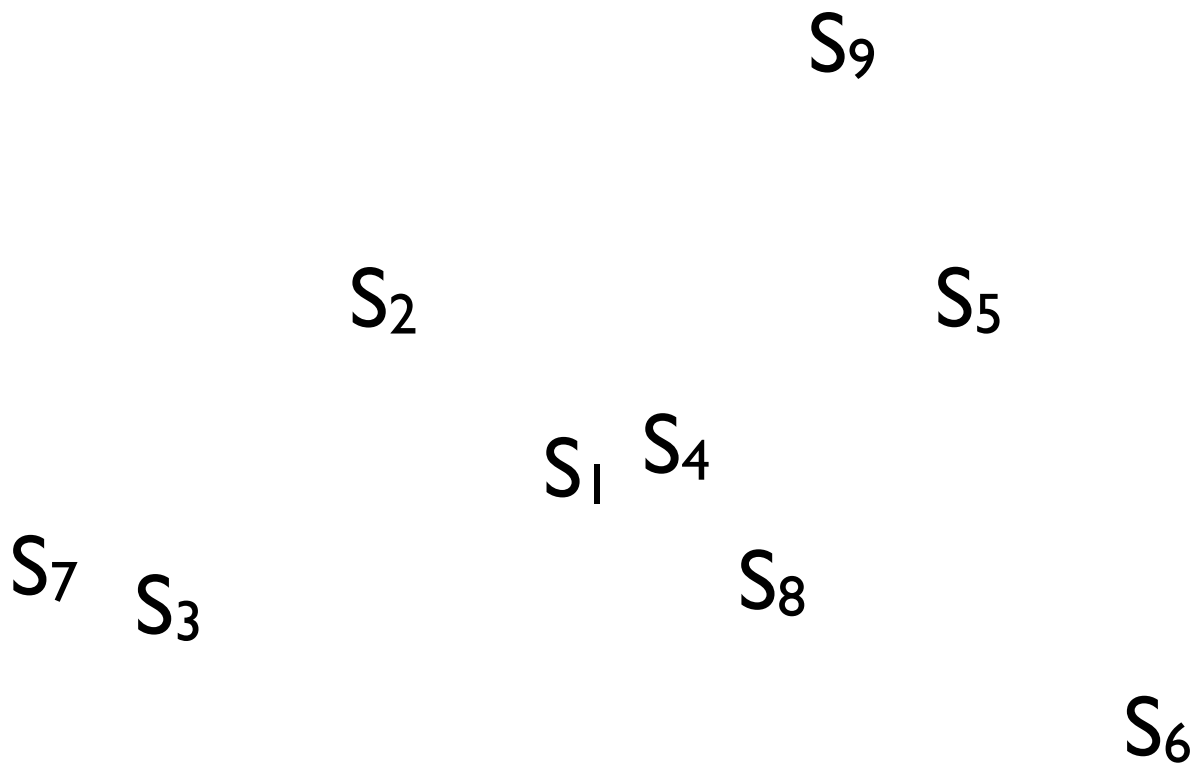

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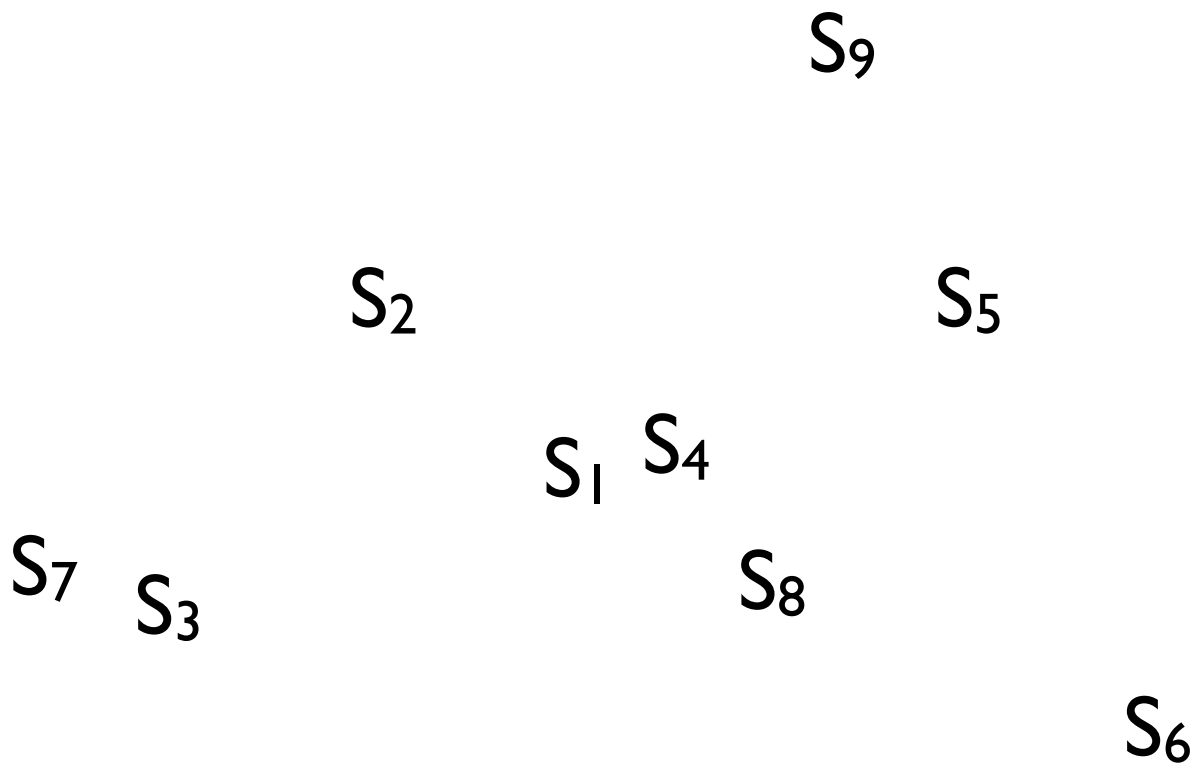

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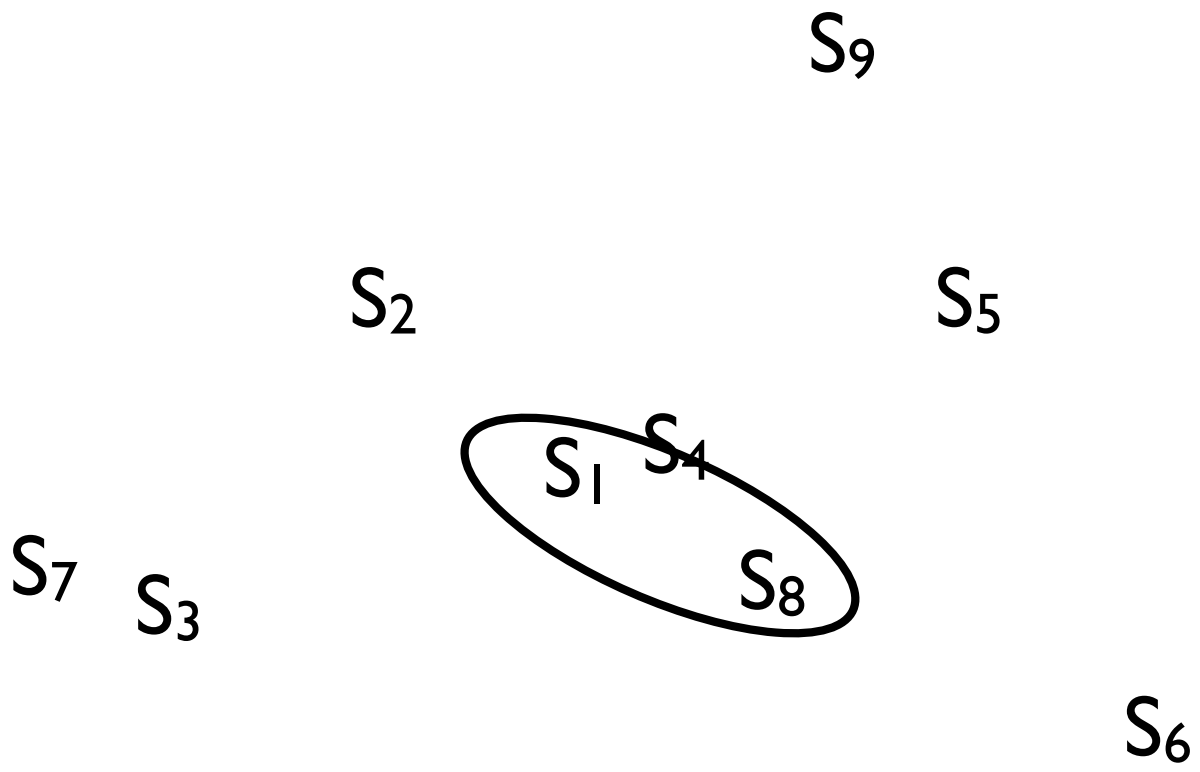

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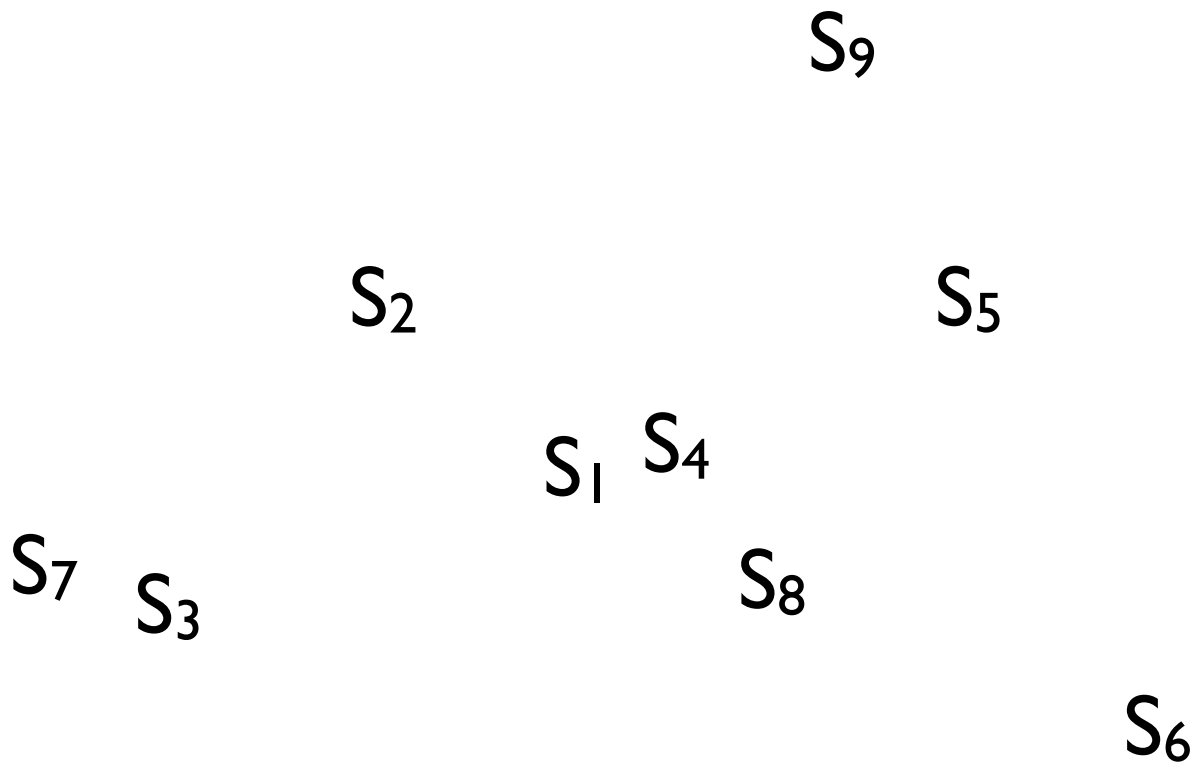


$$\underset{i \in D \setminus S}{\operatorname{argmax}} \left[ \lambda \cdot \operatorname{sim}(S_i, D) - (1 - \lambda) \cdot \max_j \left( \operatorname{sim}(S_i, S_j) \right) \right]$$

[Carbonell and Goldstein, 1998]

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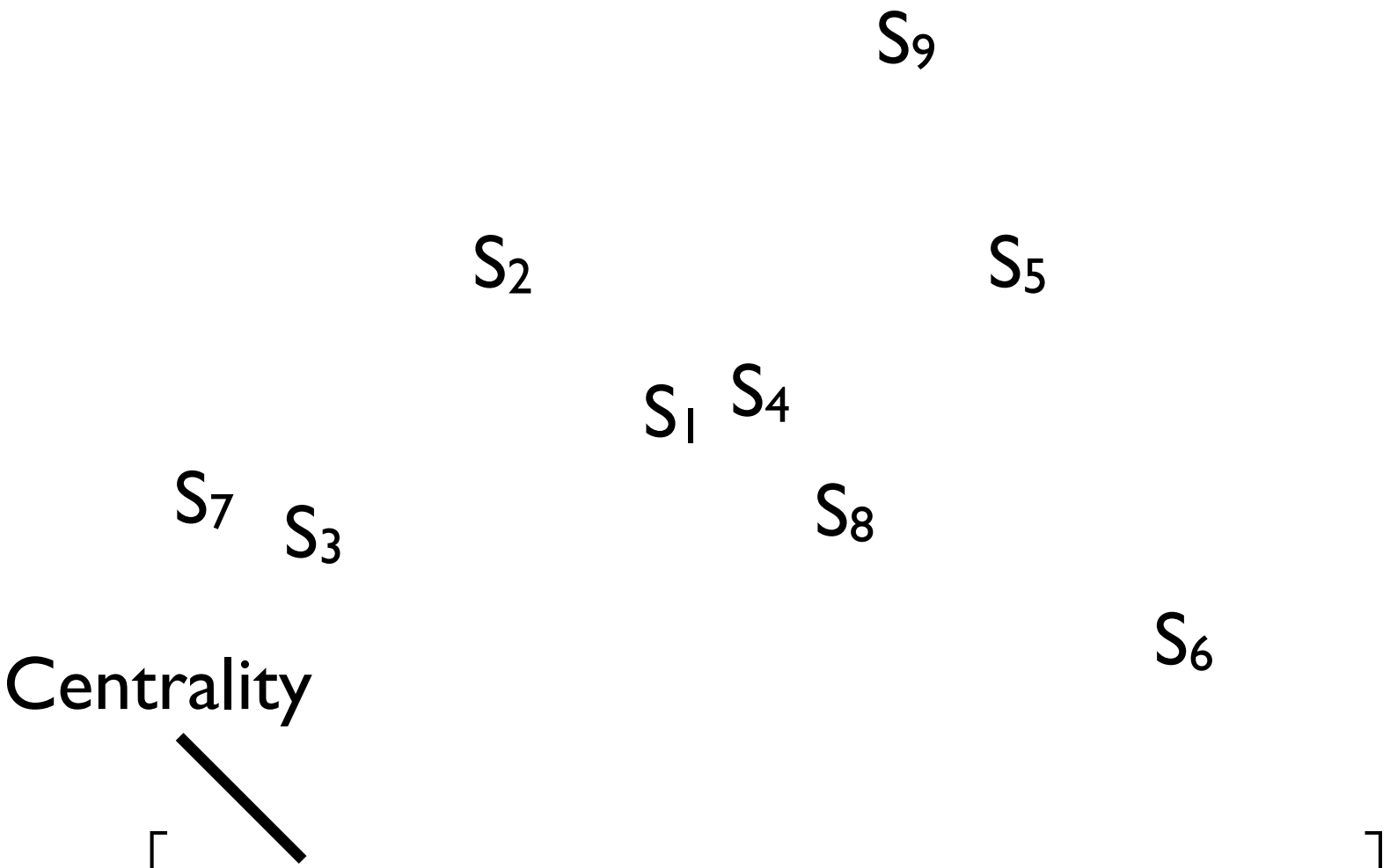


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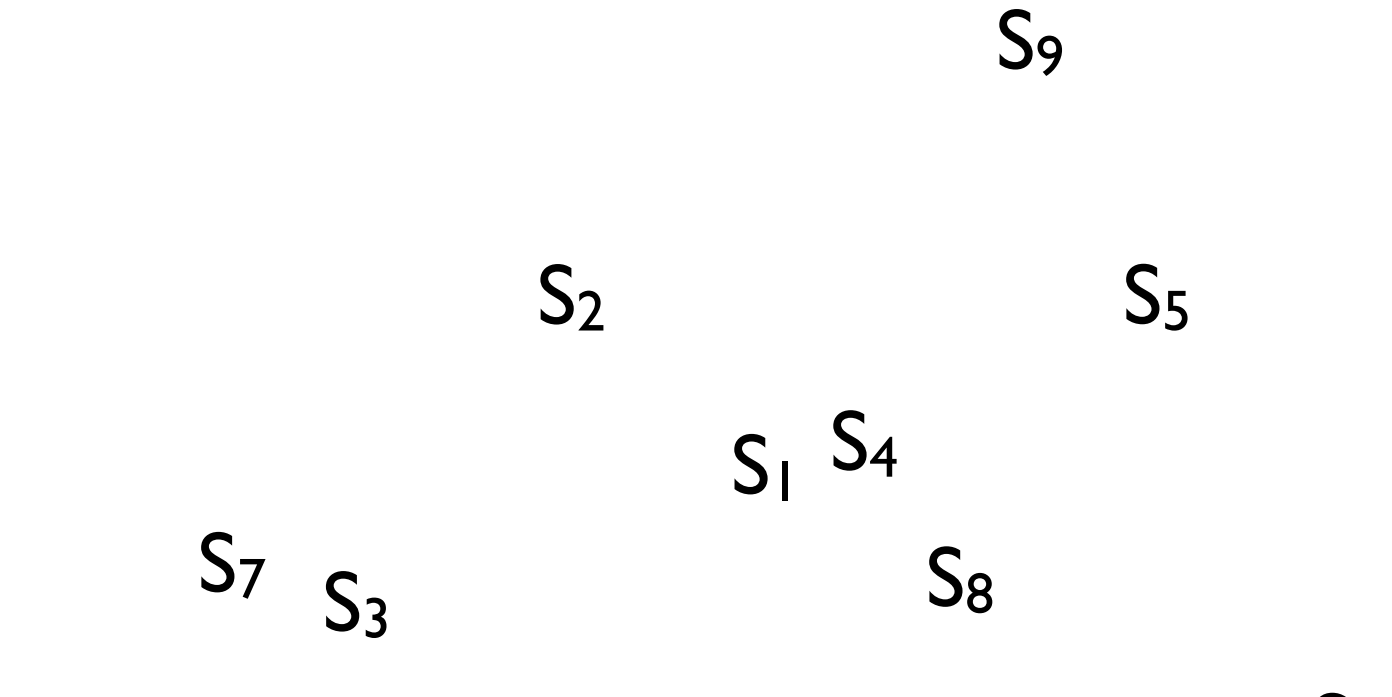


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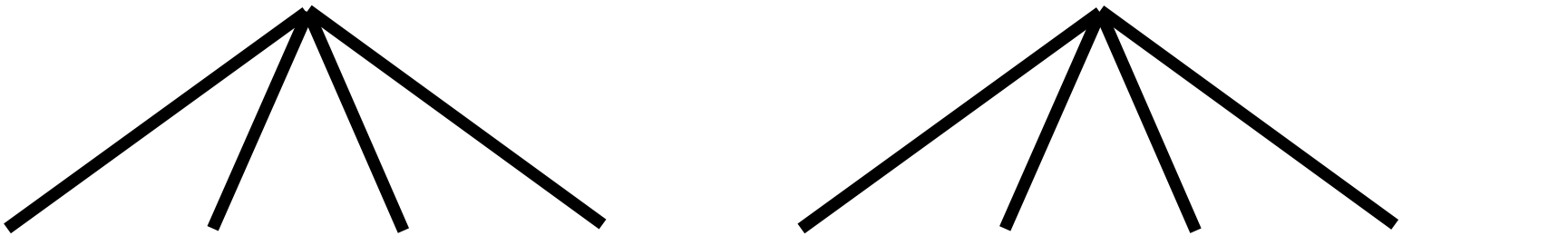
# Max Coverage

She stopped in France. In France she remained.

# Max Coverage



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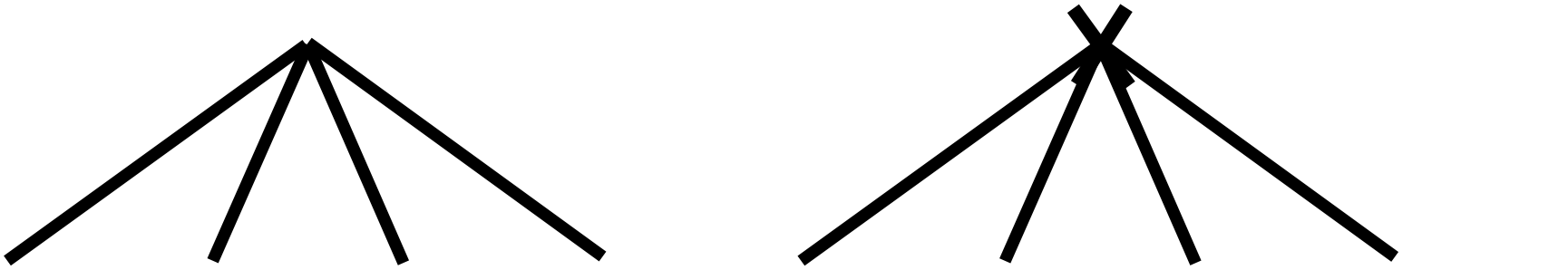

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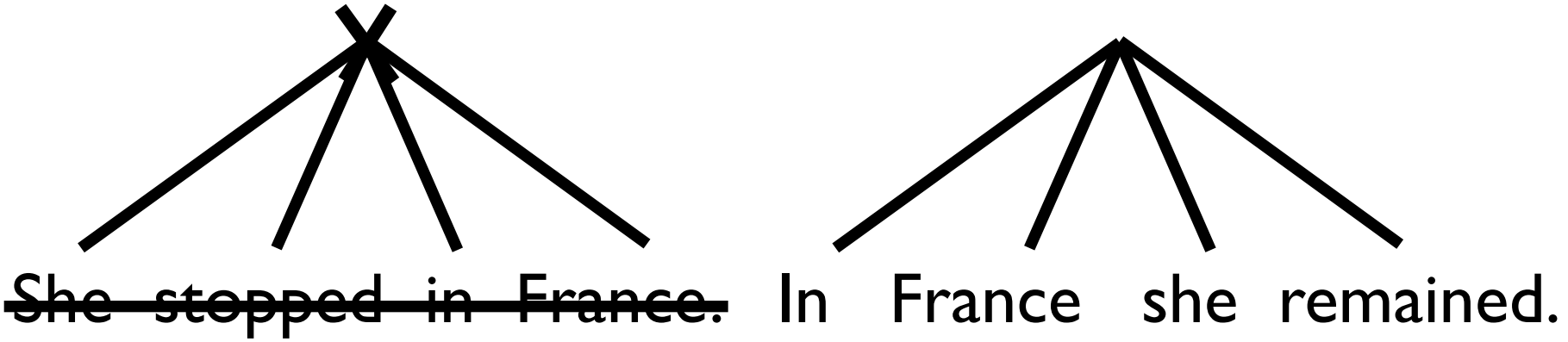
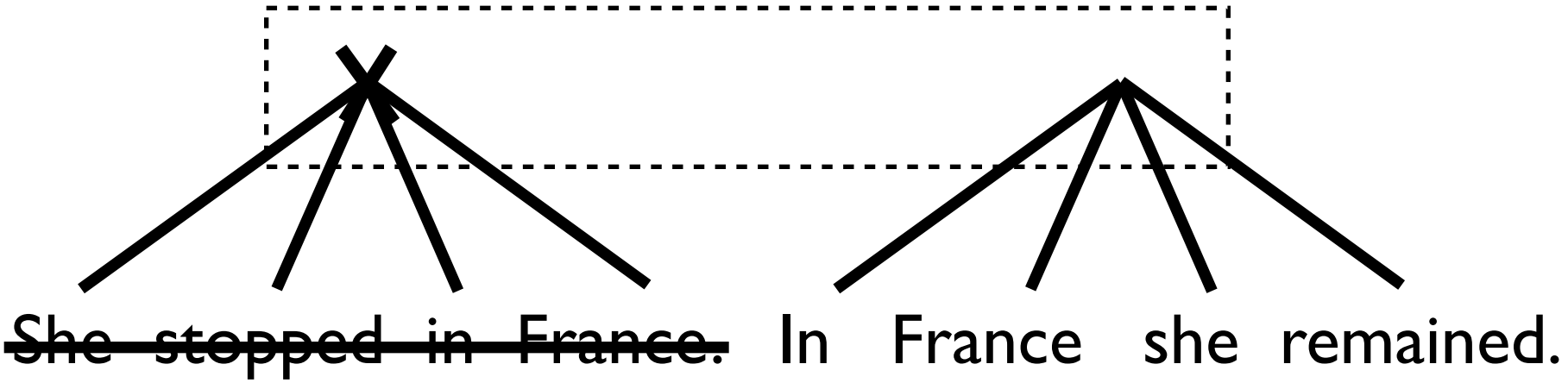


# Max Coverage

A summary is a set of cuts: $S$



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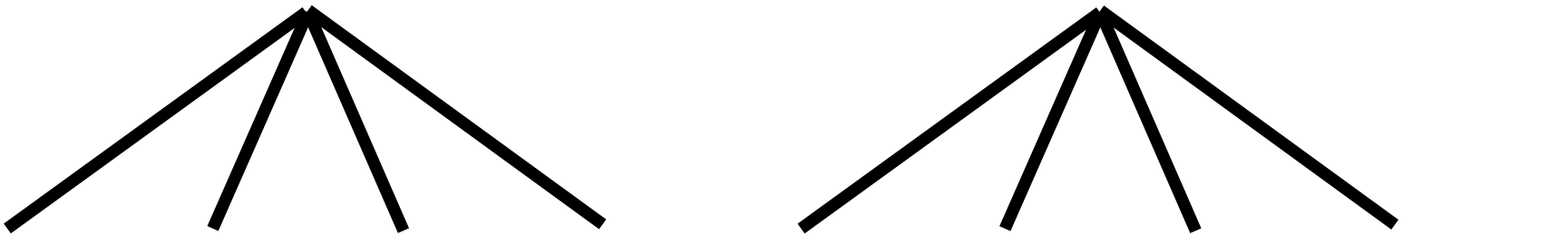

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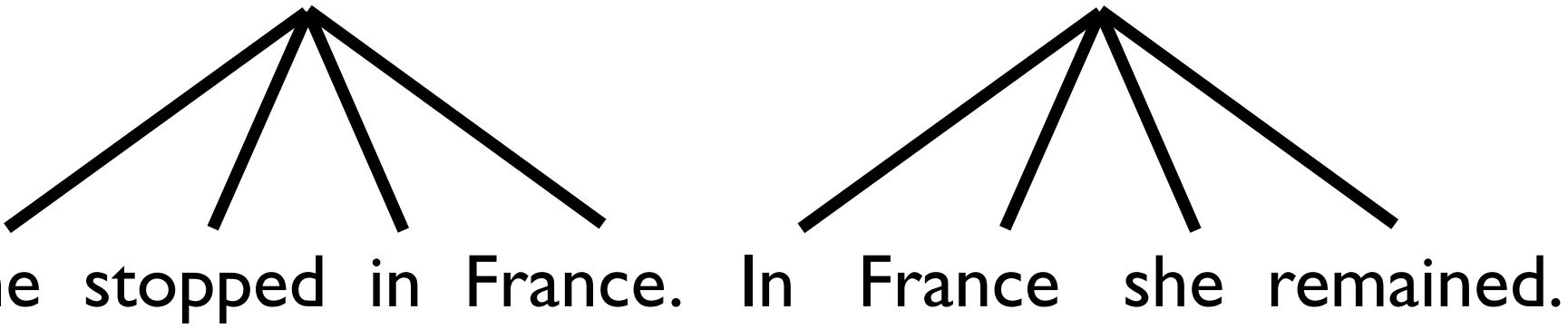


(she, stopped) ✓
(stopped, in) ✓
(in, france) ✓
(france, she) ✓
(she, remained) ✓

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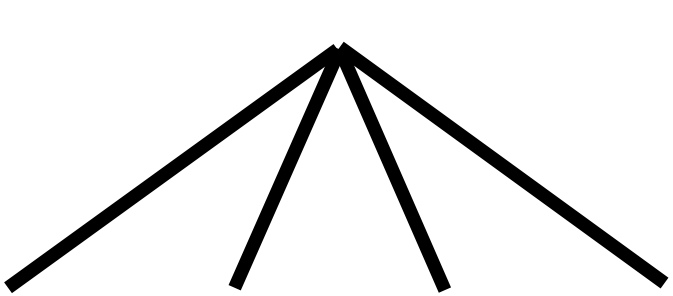

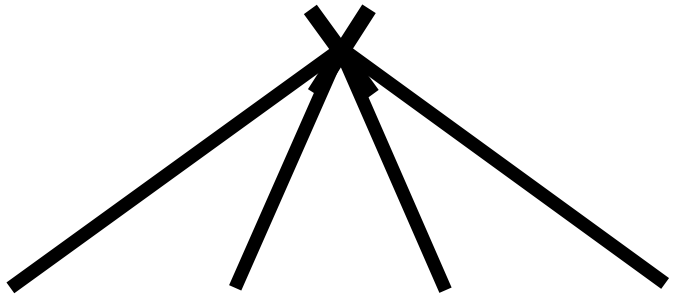

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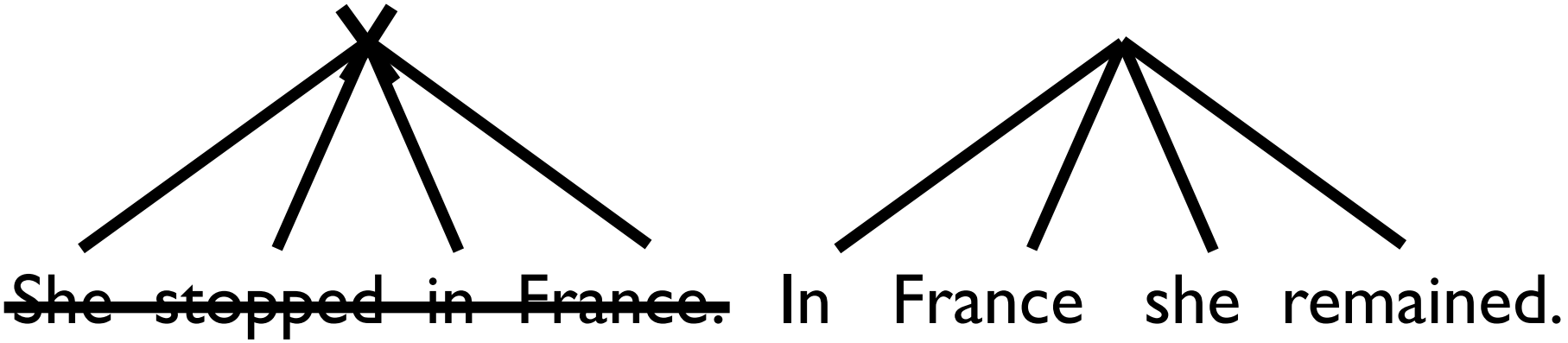


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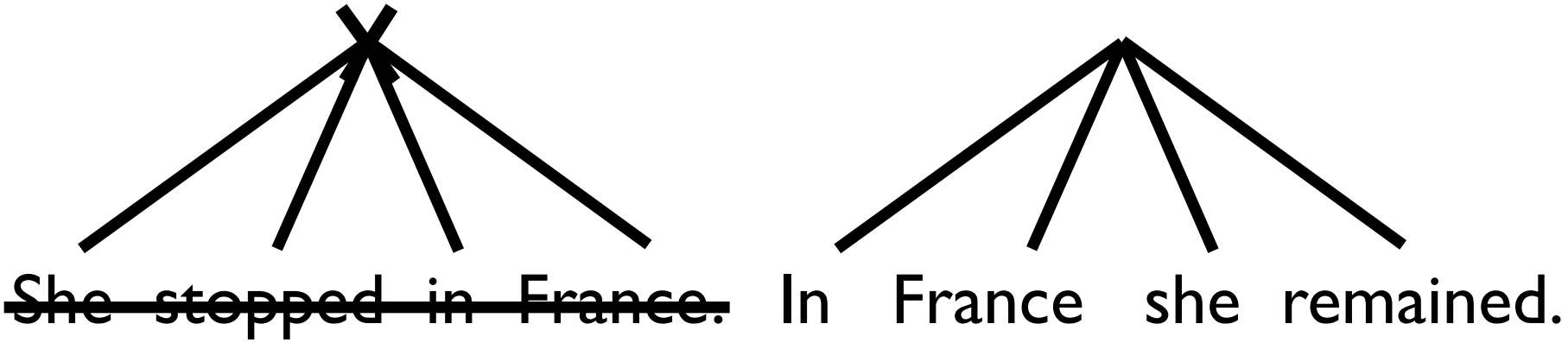


(she, stopped) (stopped, in) (in, france) ✓ (france, she) ✓ (she, remained) ✓

Set of bigrams covered by summary: $B(s)$


# Max Coverage

$$\max_{s} \ \text{coverage}(s)$$


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$$s.t. \quad \text{length}(s) \leq L_{max}$$

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# Max Coverage

$$\max_{s} \sum_{b \in B(s)} \text{value}(b)$$

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Berkeley NLP

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$$\max_{s} \sum_{b \in B(s)} \text{value}(b)$$

$$s.t. \quad \text{length}(s) \leq L_{max}$$

$$\text{value}(b) = \text{freq}(b)$$

Berkeley NLP

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[Gillick and Favre 2008]

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N L P

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N L P

# ILP for Decoding

$$\max_{s} \sum_{b \in B(s)} \text{value}(b)$$

$$s.t. \quad \text{length}(s) \leq L_{max}$$

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# ILP for Decoding

$$\max_{s,z} \sum_{b} z_b \cdot \text{value}(b)$$

$$s.t. \quad \text{length}(s) \leq L_{max}$$

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$$s.t. \quad \text{length}(s) \leq L_{max}$$

bigrams in $s$ are covered

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$$s.t. \quad \text{length}(s) \leq L_{max}$$

bigrams in $s$ are covered

only bigrams in $s$ are covered

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# ILP for Decoding

$$\max_{s,z} \sum_b z_b \cdot \text{value}(b)$$

$$s.t. \quad \sum_n l_n s_n \leq L_{\max}$$

$$\forall_{n,b} \quad s_n Q_{nb} \leq z_b$$

$$\forall_b \quad \sum_n s_n Q_{nb} \geq z_b$$

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# Linear Model for Extraction

$$\max_{s} \sum_{b \in B(s)} \text{value}(b)$$

$$s.t. \quad \text{length}(s) \leq L_{max}$$

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Berkeley
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# Linear Model for Extraction

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Parameterize using features:

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The Mean Girls star is due back in court on Feb. 23 an important hearing in which Lohan could opt to end the case early.

# Extraction and Compression




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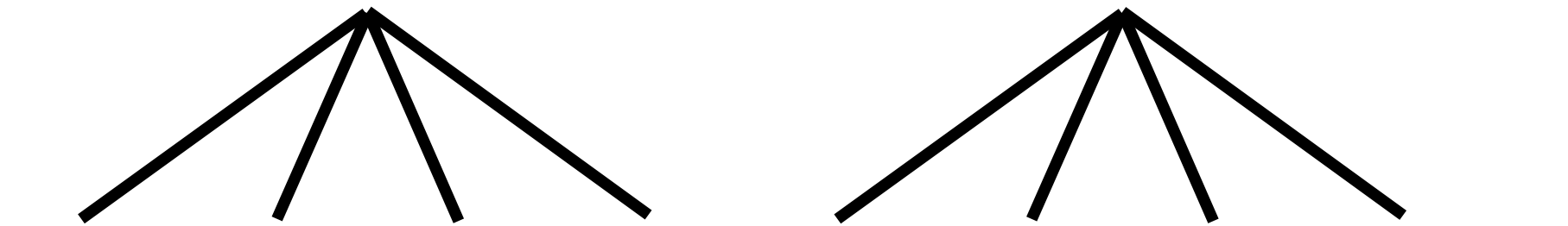
[Martins and Smith 2009]
[Woodsend and Lapata 2010]


# Extraction and Compression

She stopped in France. ~~In France~~ she remained.

# Joint Extractive / Compressive Model



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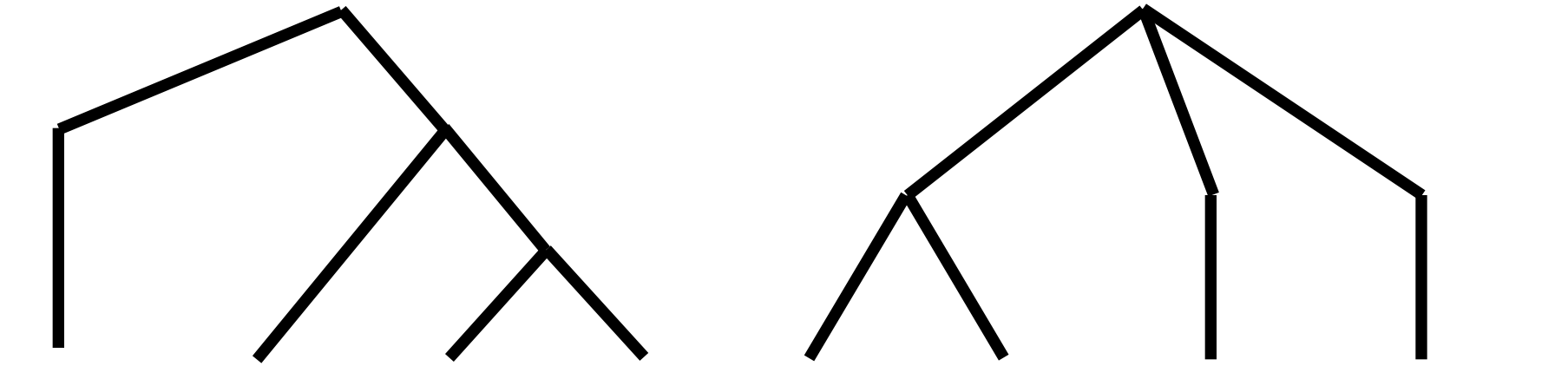

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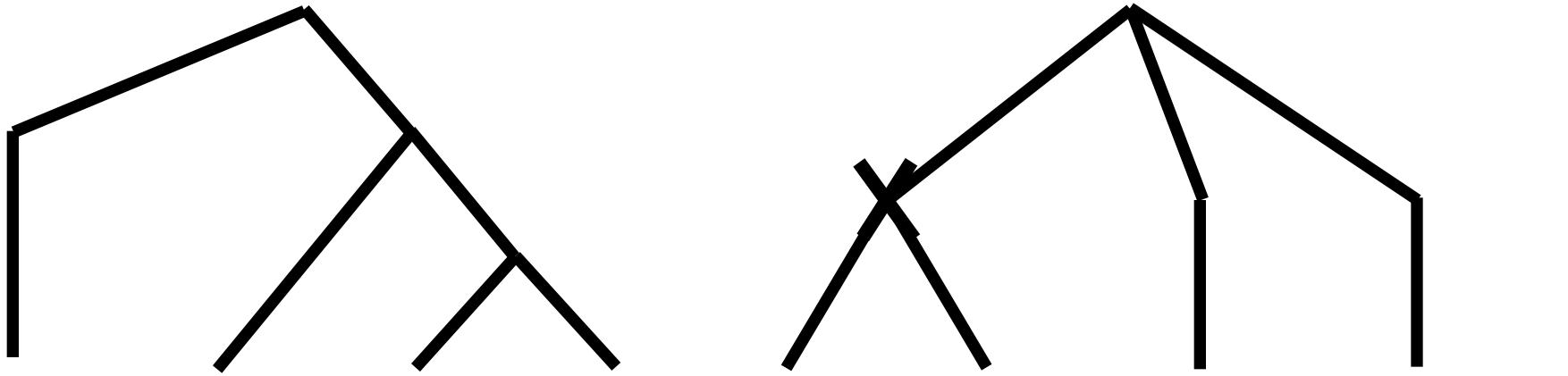

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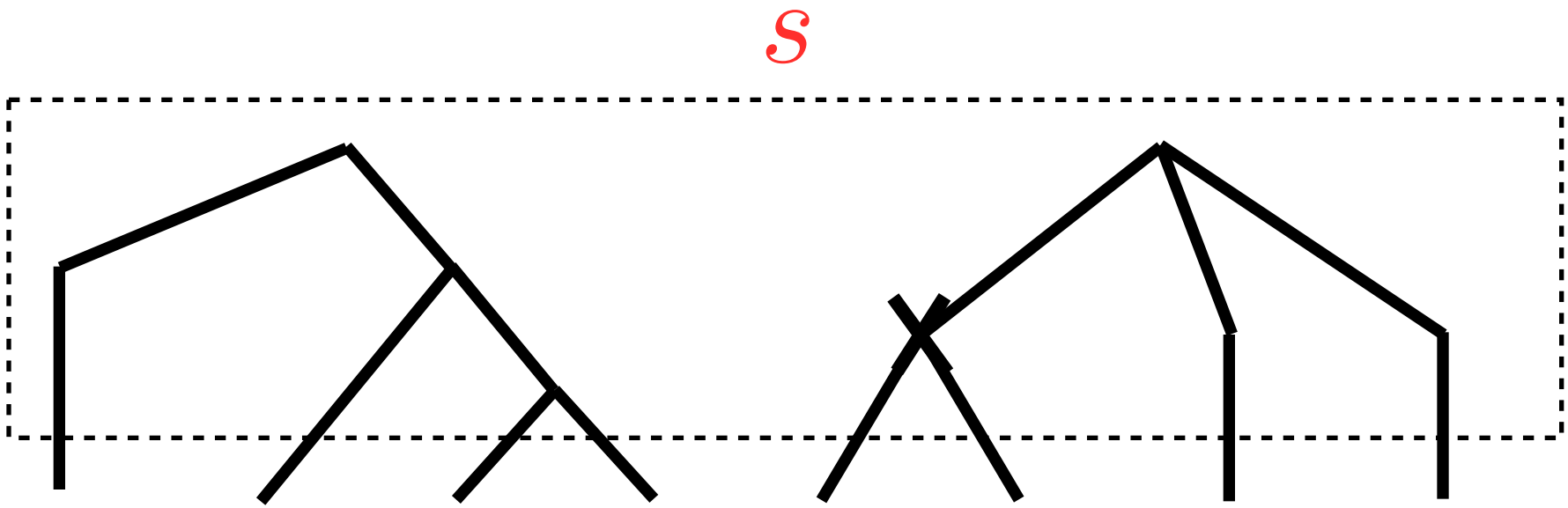

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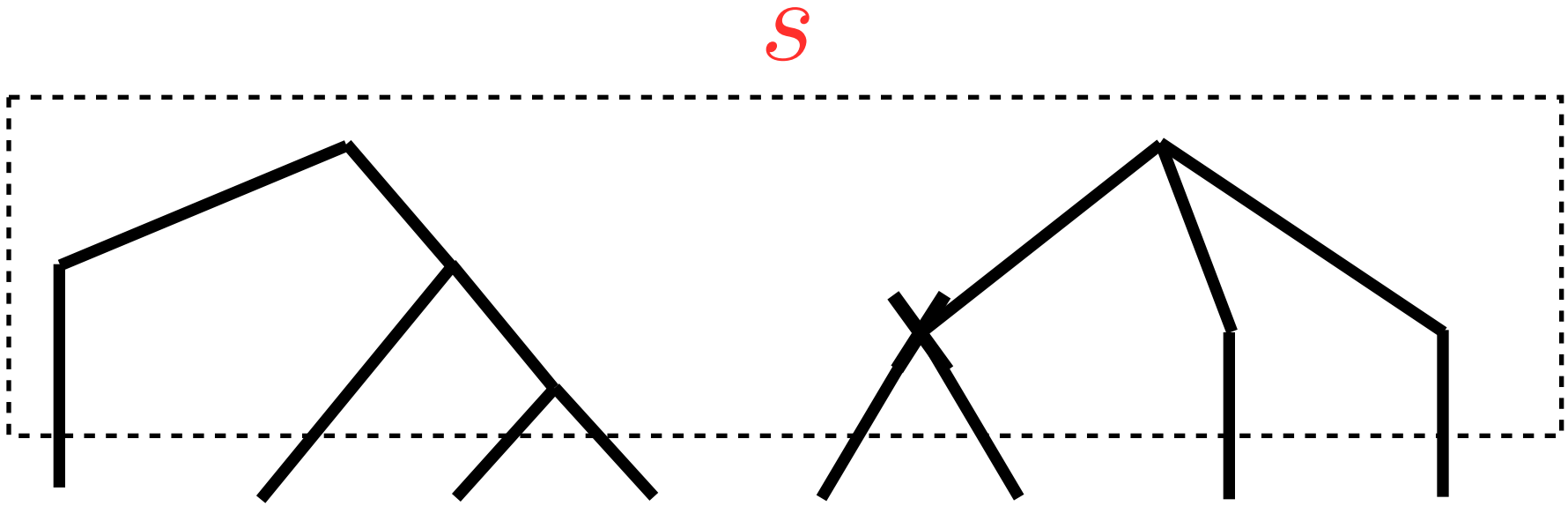


(she, stopped) ✓ (in, france) ✓ (she, remained) ✓

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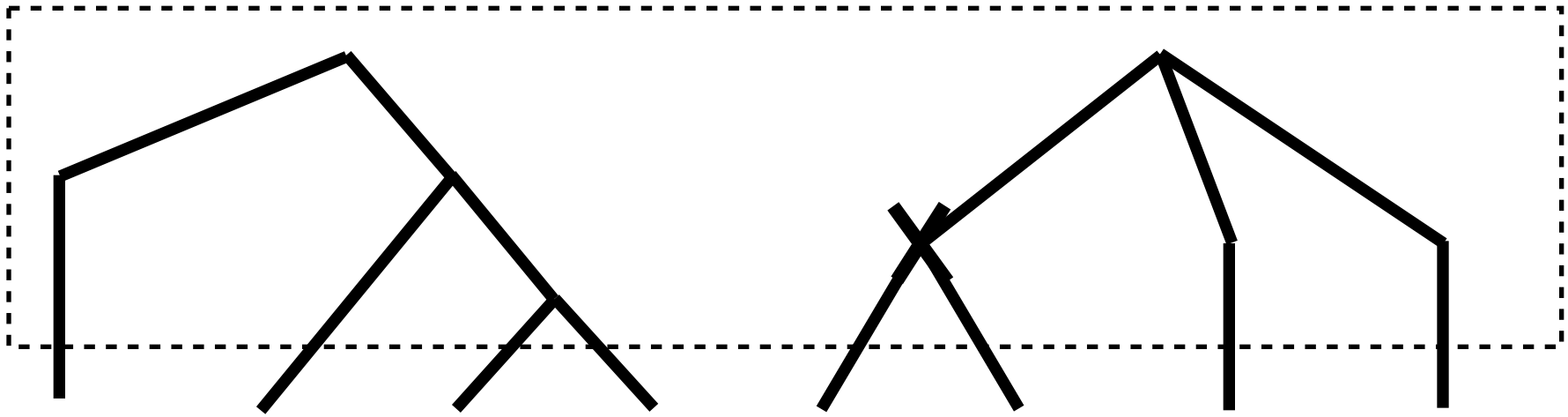
# Joint Extractive / Compressive Model

$s$



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$B(s)$

# Joint Extractive / Compressive Model

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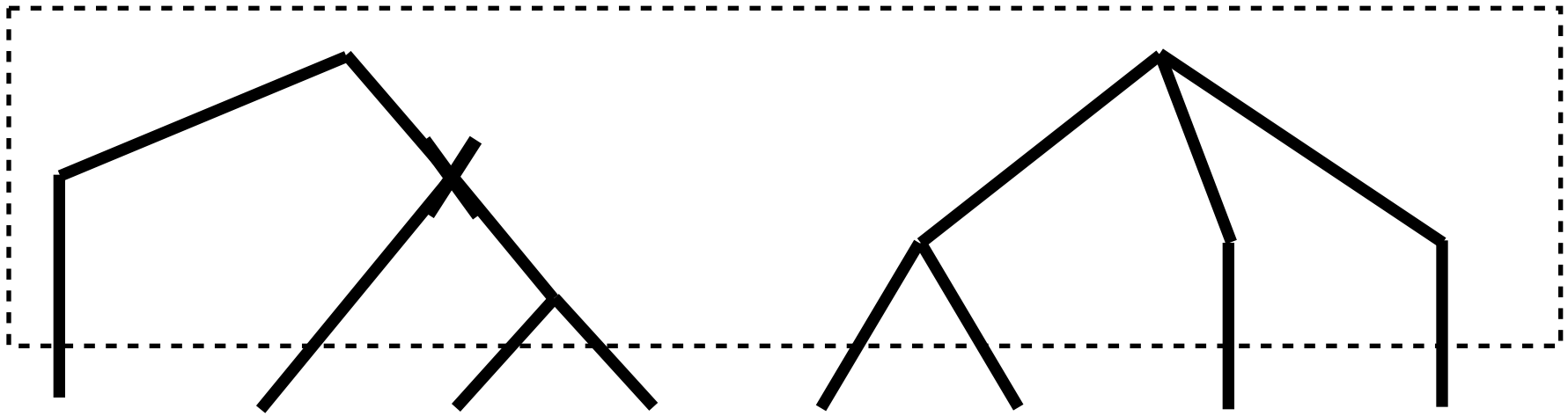


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$B(s)$


# Joint Extractive / Compressive Model

$$\max_{s} \left[ \sum_{b \in B(s)} \text{value}(b) \right]$$


# Joint Extractive / Compressive Model

$$\max_{s} \left[ \sum_{b \in B(s)} \text{value}(b) + \sum_{c \in s} \text{value}(c) \right]$$

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# Joint Extractive / Compressive Model

$$\max_{s} \left[ \sum_{b \in B(s)} \text{value}(b) + \sum_{c \in s} \text{value}(c) \right]$$

Parameterize using features:

$$\text{value}(b) = w^\top f(b)$$

$$\text{value}(c) = w^\top f(c)$$


# Learning

Linear prediction:

$$\text{score}(s) = w^\top f(s)$$

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# Learning

Linear prediction:

$$\text{score}(s) = w^\top f(s)$$

Feature function factors:

$$f(s) = \sum_{b \in B(s)} f(b) + \sum_{c \in s} f(c)$$


# Features


# Features

Bigram Features $f(b)$


# Features

Bigram Features $f(b)$

Cut Features $f(c)$


# Features

## Bigram Features $f(b)$

## Cut Features $f(c)$

| | |
|---|---|
| COUNT: | Bucketed document counts |
| STOP: | Stop word indicators |
| POSITION: | First document position indicators |
| CONJ: | All two- and three-way conjunctions of above |
| BIAS: | Always one |

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# Features

## Bigram Features $f(b)$

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| POSITION: | First document position indicators |
| CONJ: | All two- and three-way conjunctions of above |
| BIAS: | Always one |

## Cut Features $f(c)$

| | |
|---|---|
| COORD: | Coordinated phrase, four versions: NP, VP, S, SBAR |
| S-ADJUNCT: | Adjunct to matrix verb, four versions: CC, PP, ADVP, SBAR |
| REL-C: | Relative clause indicator |
| ATTR-C: | Attribution clause indicator |
| ATTR-PP: | PP attribution indicator |
| TEMP-PP: | Temporal PP indicator |
| TEMP-NP | Temporal NP indicator |
| BIAS: | Always one |

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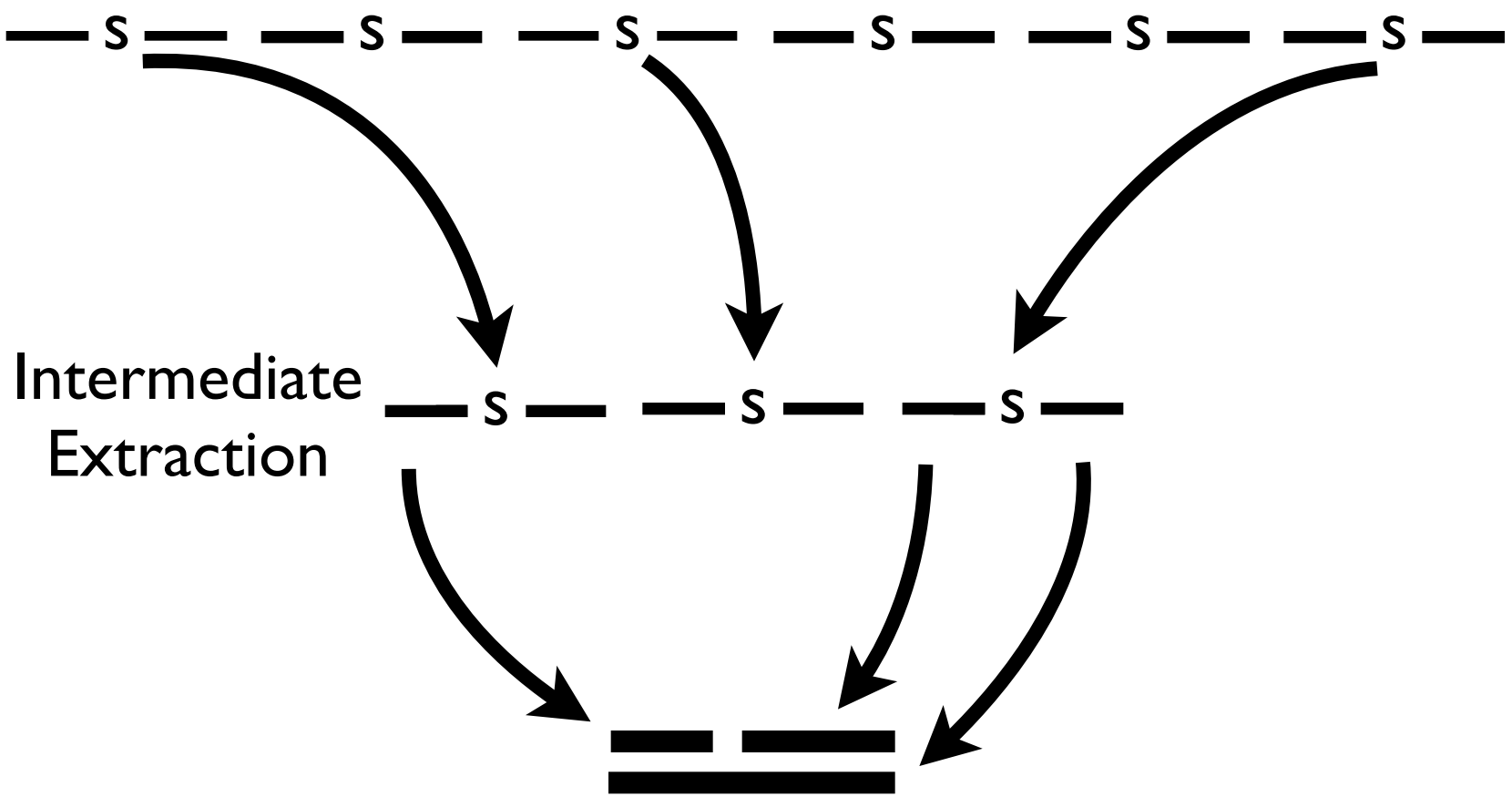
# Obtaining Training Data




Lindsay Lohan pleaded not guilty ~~Wednesday~~ to felony grand theft of a 2,500 necklace, ~~a case that could return the troubled starlet to jail rather than the big screen.~~ Saying it appeared that Lohan had violated her probation in a 2007 drunken driving case the judge set bail at $40,000 ~~and warned that if Lohan was accused of breaking the law while free he would have her held without bail~~. The Mean Girls star is due back in court on Feb. 23 ~~an important hearing in which Lohan could opt to end the case early.~~

# Obtaining Training Data

TAC 2009: 44 Document Collections



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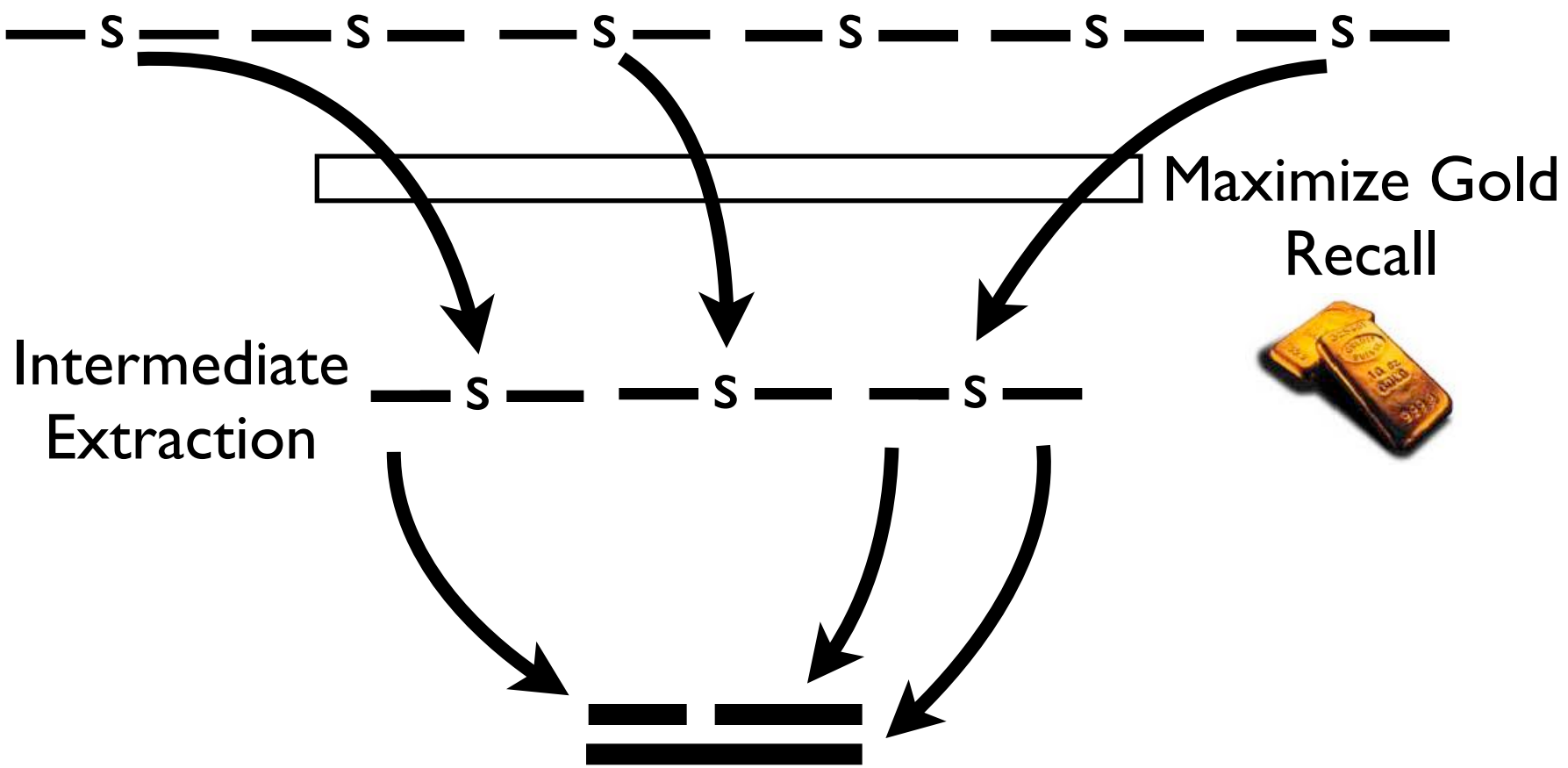

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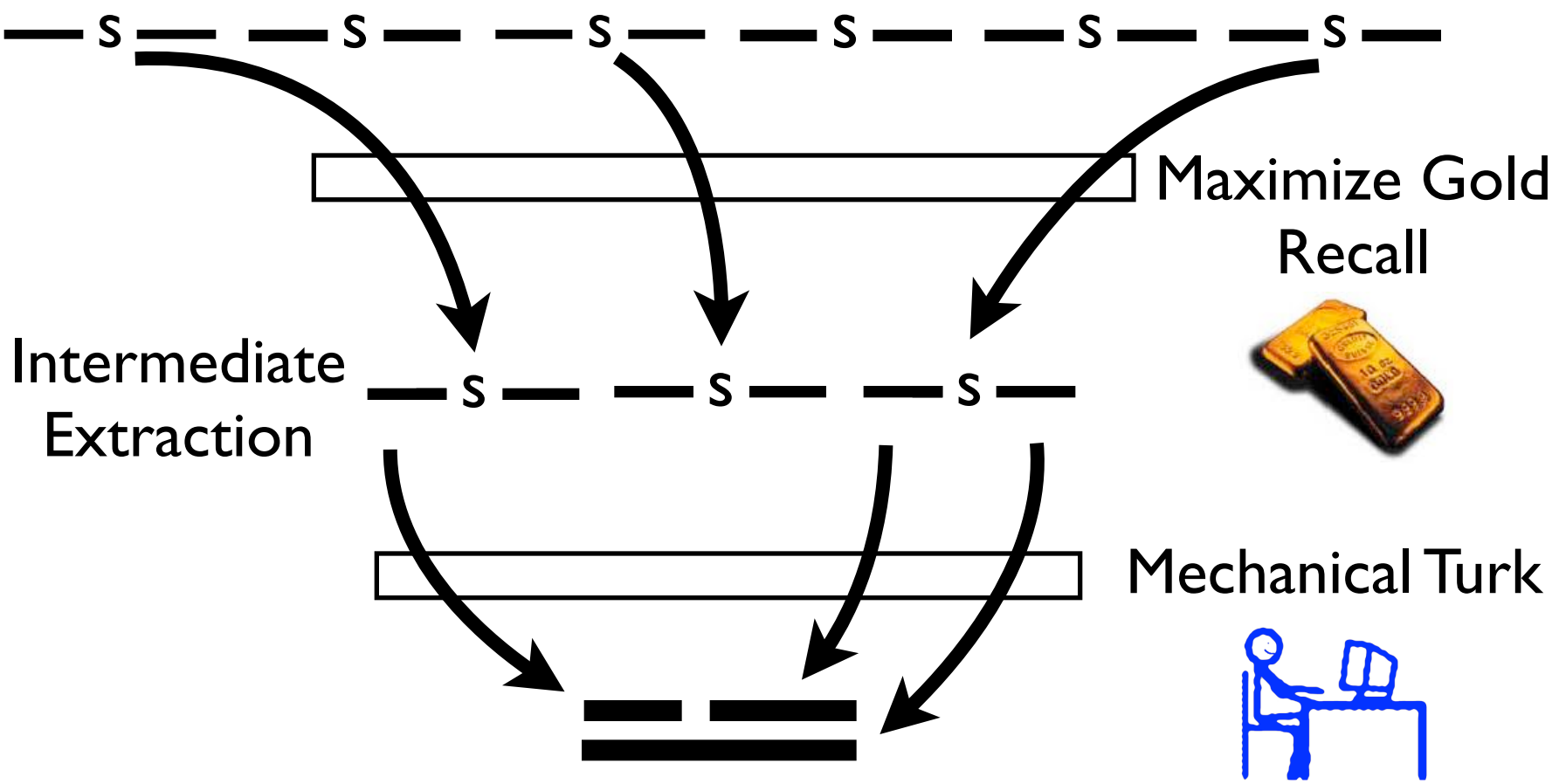


# Learning


# Learning

Structured SVM Training:

Berkeley NLP

# Learning

Structured SVM Training:

$$\min_{w} \quad \|w\|_2^2$$

Berkeley NLP

# Learning

Structured SVM Training:

$$\min_{w} \quad \|w\|_2^2$$

$s.t.$ for all possible guess summaries:

score of gold exceeds score of guess by loss

Berkeley NLP

# Learning

Structured SVM Training:

$$\min_{w} \quad \|w\|_2^2$$

$s.t.$ for all possible guess summaries:

$$w^\top f(S^*) - w^\top f(S) \geq \text{loss}(S^*, S)$$

Berkeley NLP

# Learning

Structured SVM Training:

$$\min_{w} \quad \|w\|_2^2$$

$s.t.$ for all possible guess summaries:

$$w^\top f(S^*) - w^\top f(S) \geq \text{loss}(S^*, S) - \xi$$

Berkeley NLP

# Learning

Structured SVM Training:

$$\min_{w} \left[ \|w\|_2^2 + \xi \right]$$

$s.t.$ for all possible guess summaries:

$$w^\top f(S^*) - w^\top f(S) \geq \text{loss}(S^*, S) - \xi$$

Berkeley NLP

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Structured SVM Training:

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$s.t.$ for all possible guess summaries:

$$w^\top f(S^*) - w^\top f(S) \geq \boxed{\text{loss}(S^*, S)} - \xi$$

End-to-end summarization quality

Berkeley NLP

# Learning

Structured SVM Training:

$$\min_{w} \left[ \|w\|_2^2 + \xi \right]$$

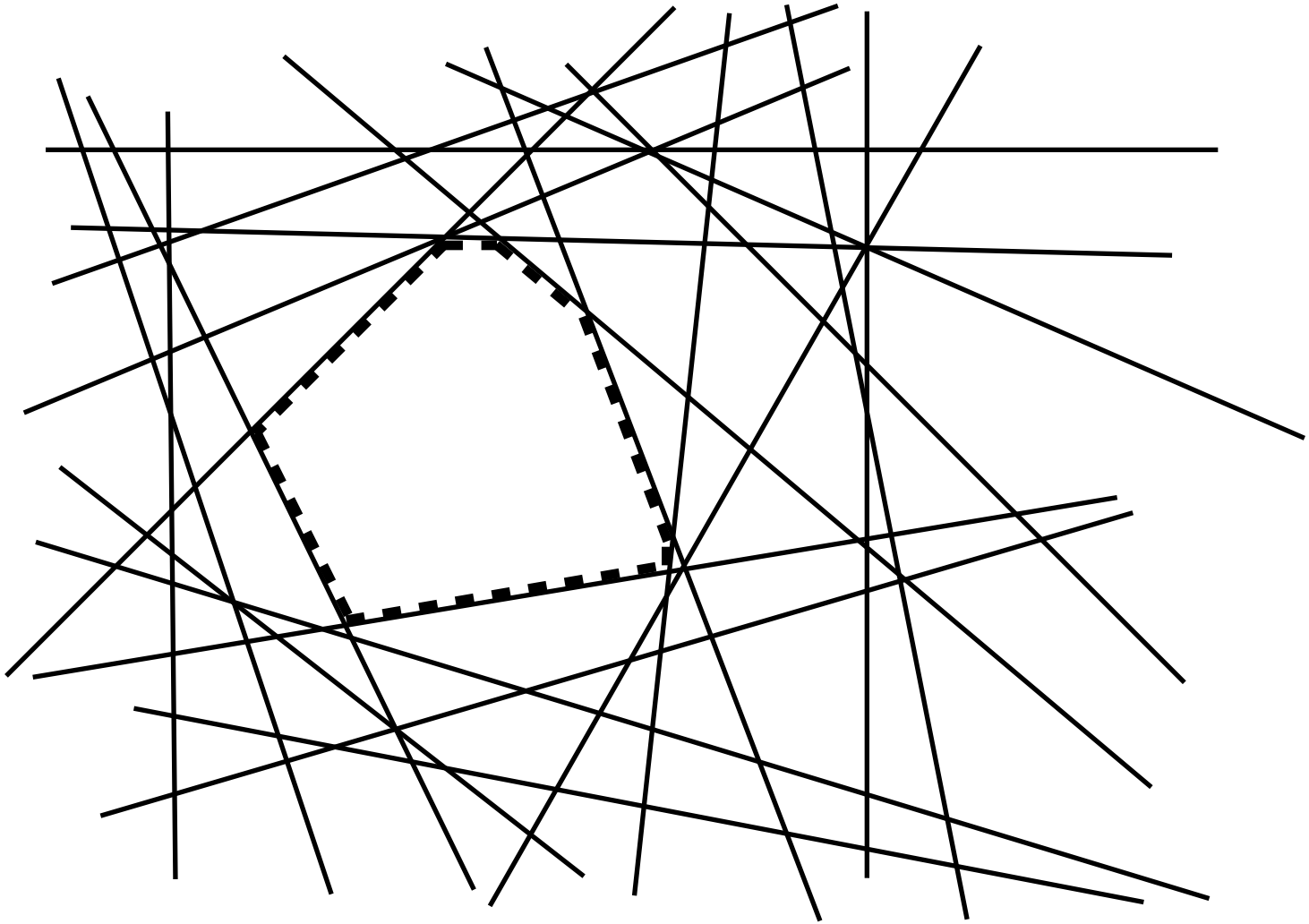
$s.t.$ for all possible guess summaries:

$$w^\top f(S^*) - w^\top f(S) \geq \text{loss}(S^*, S) - \xi$$

Exponentially many constraints!

Berkeley
N L P

# Learning



[Tsochantaridis et al. 2004]

Berkeley NLP

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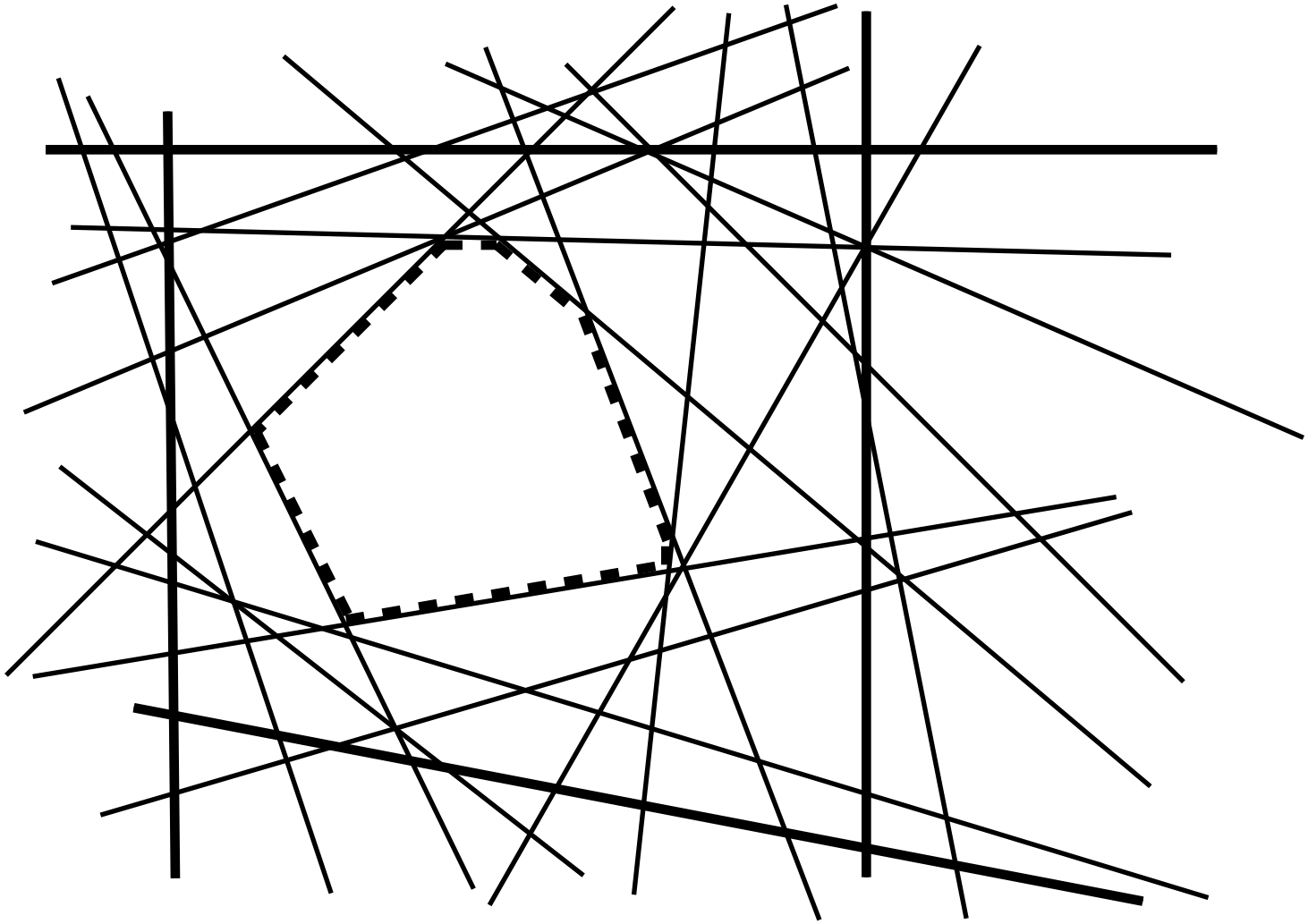

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Berkeley NLP

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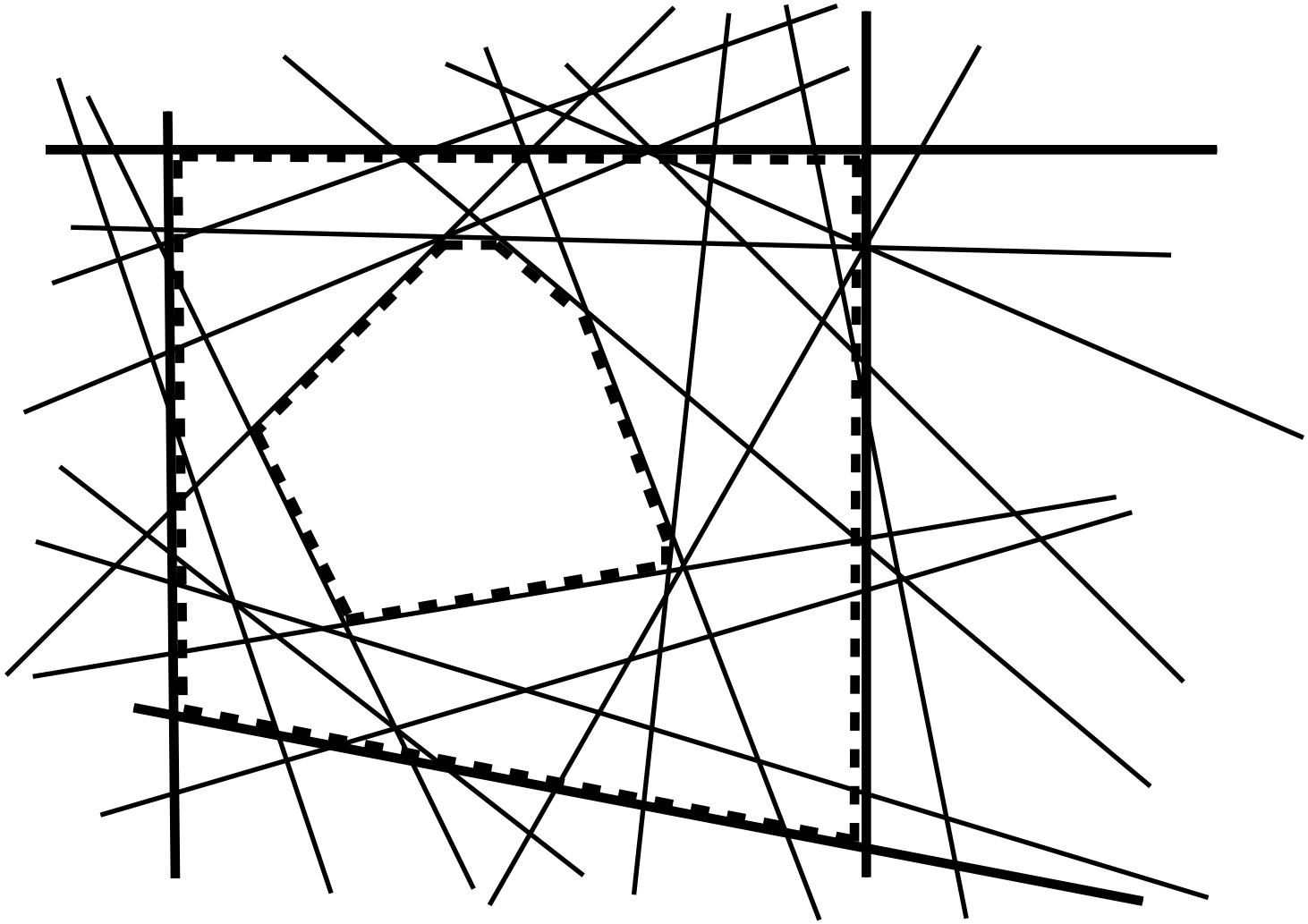

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Berkeley NLP

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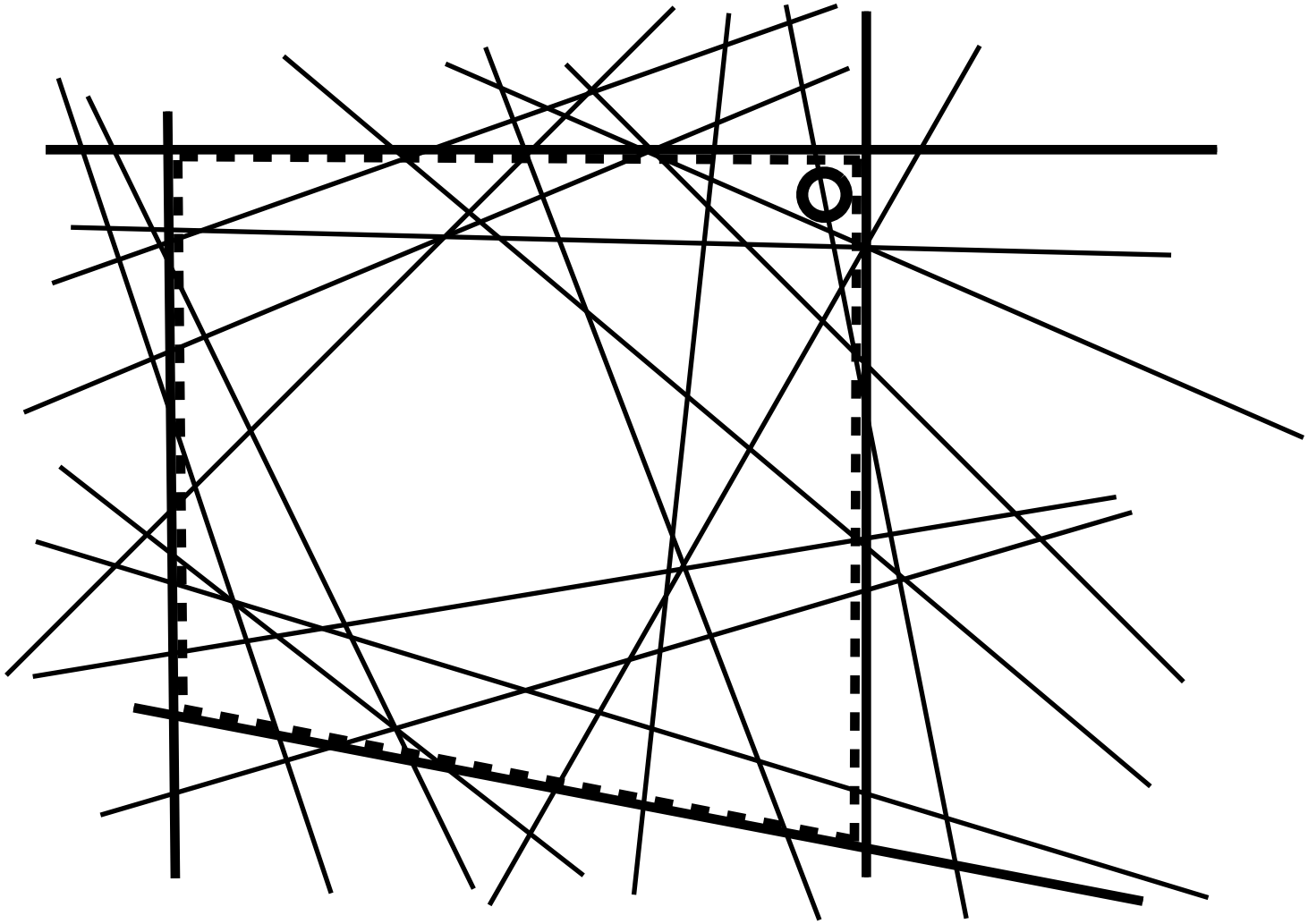


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Berkeley NLP

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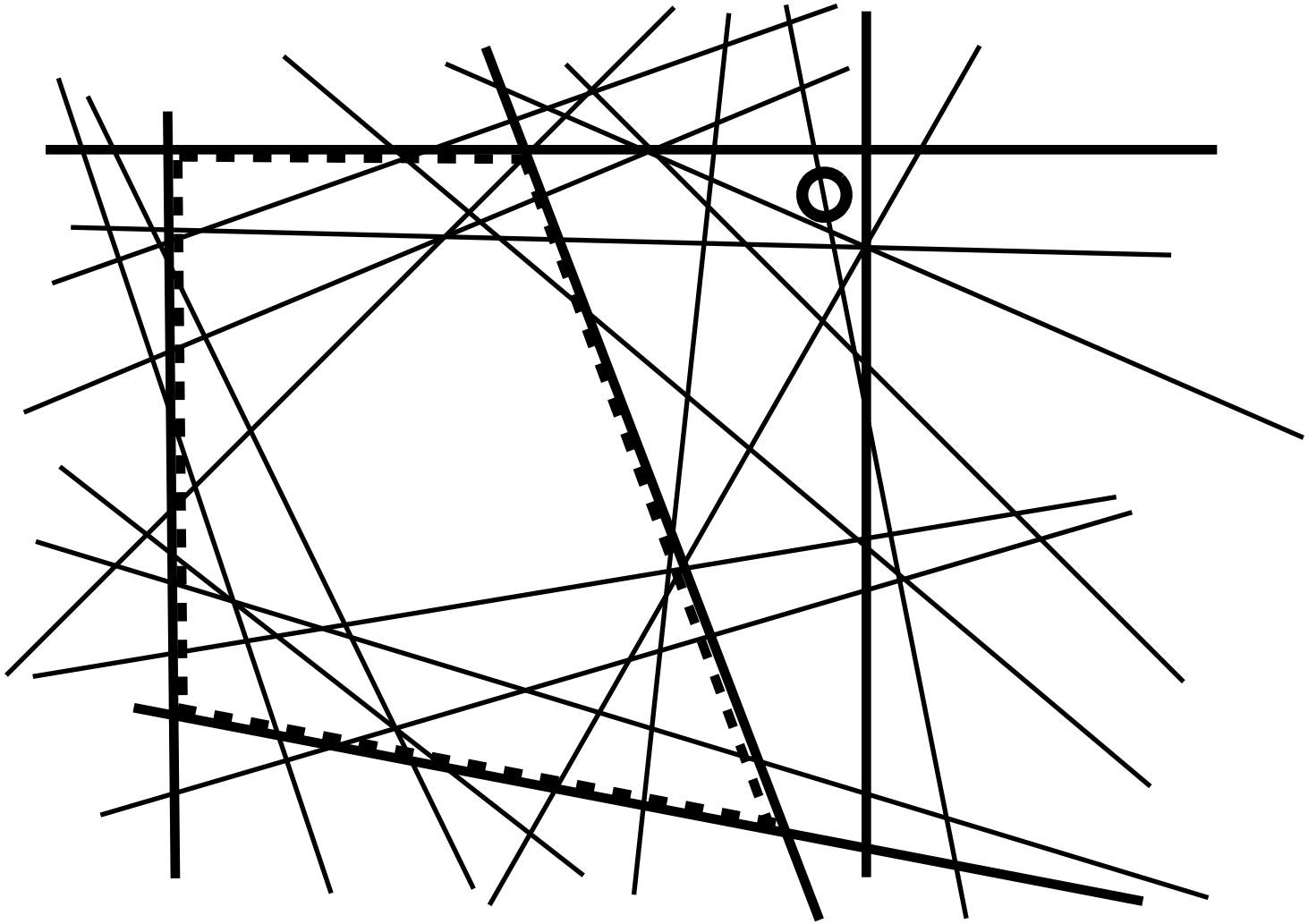

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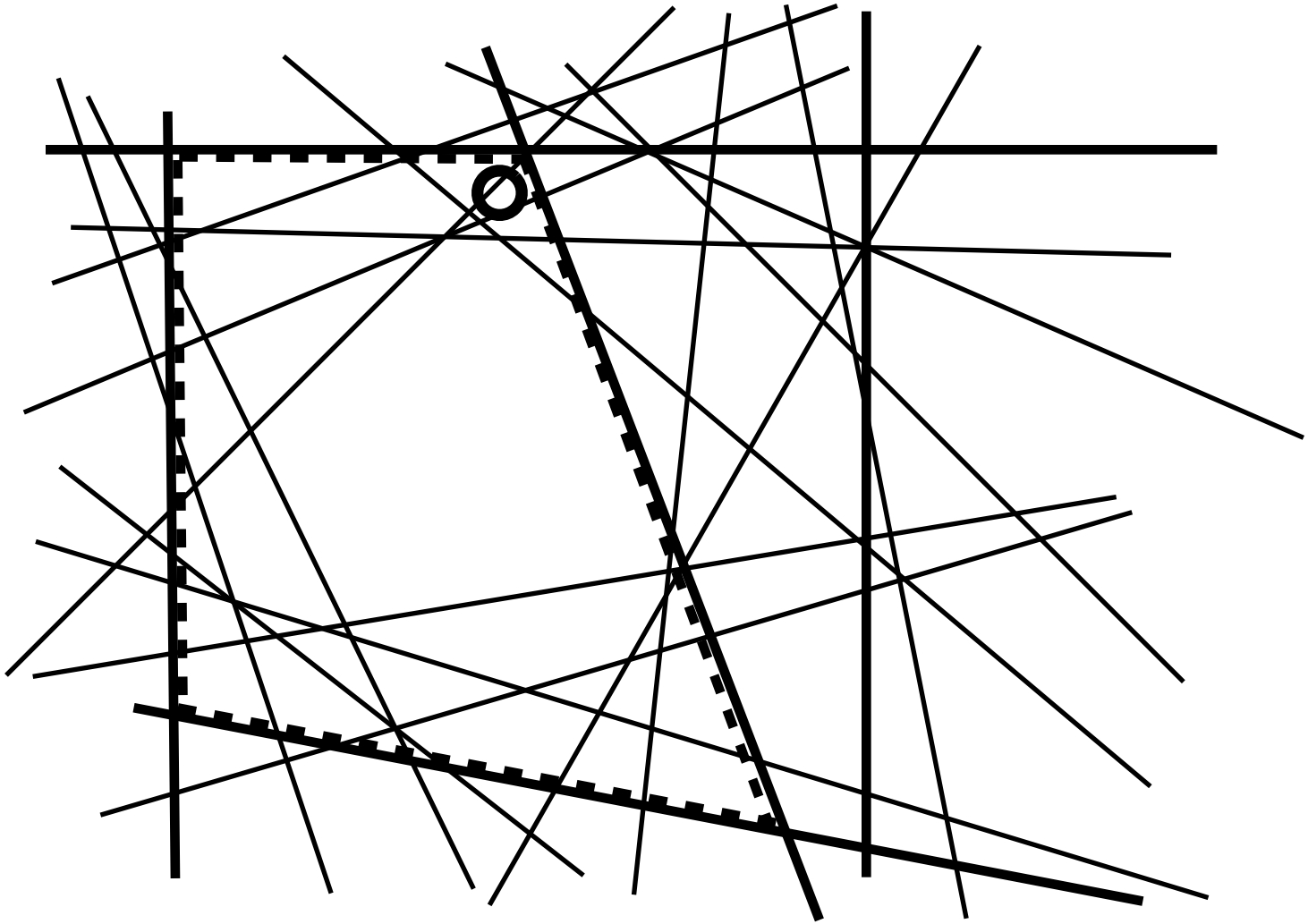

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Berkeley NLP

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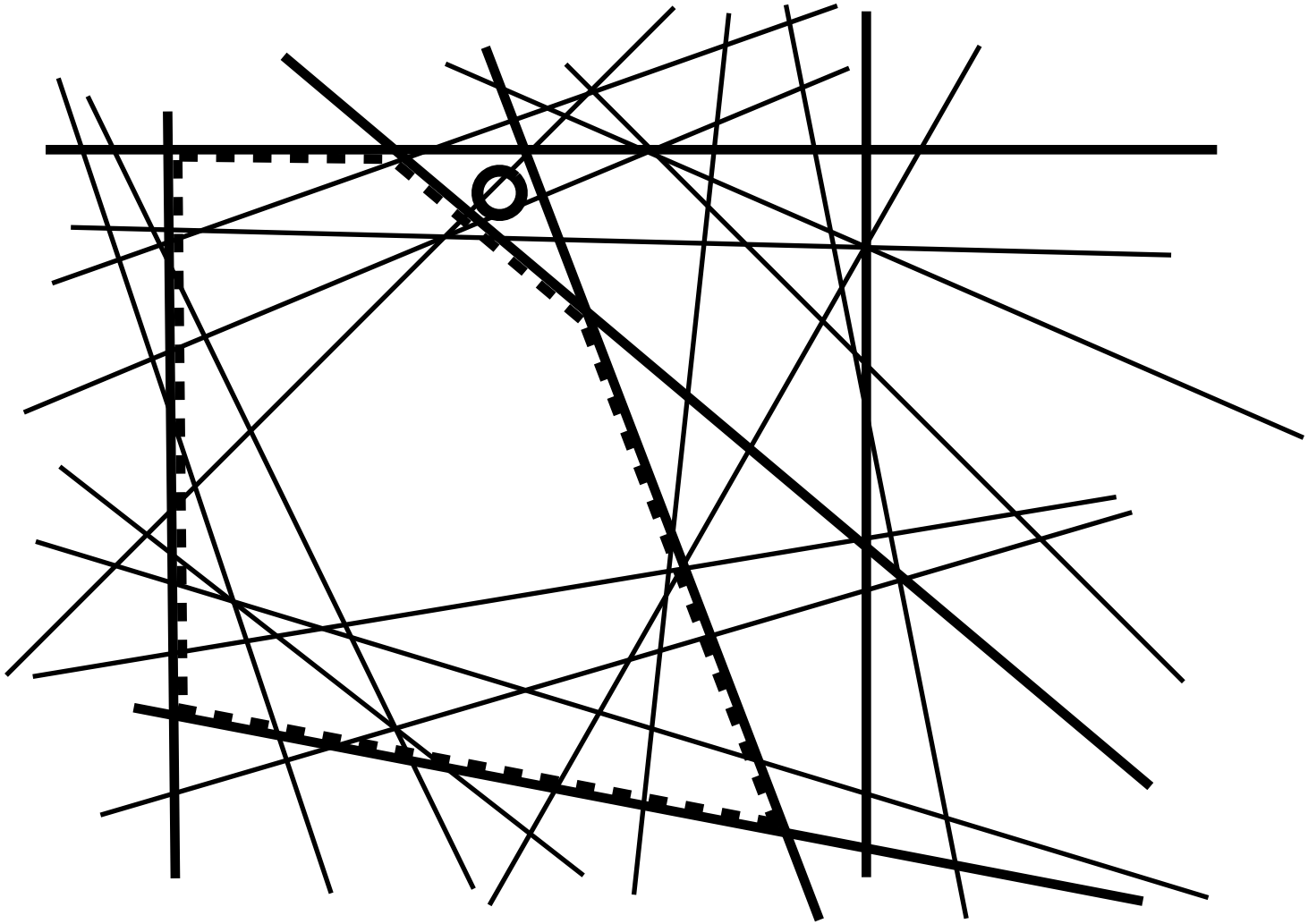

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Berkeley NLP

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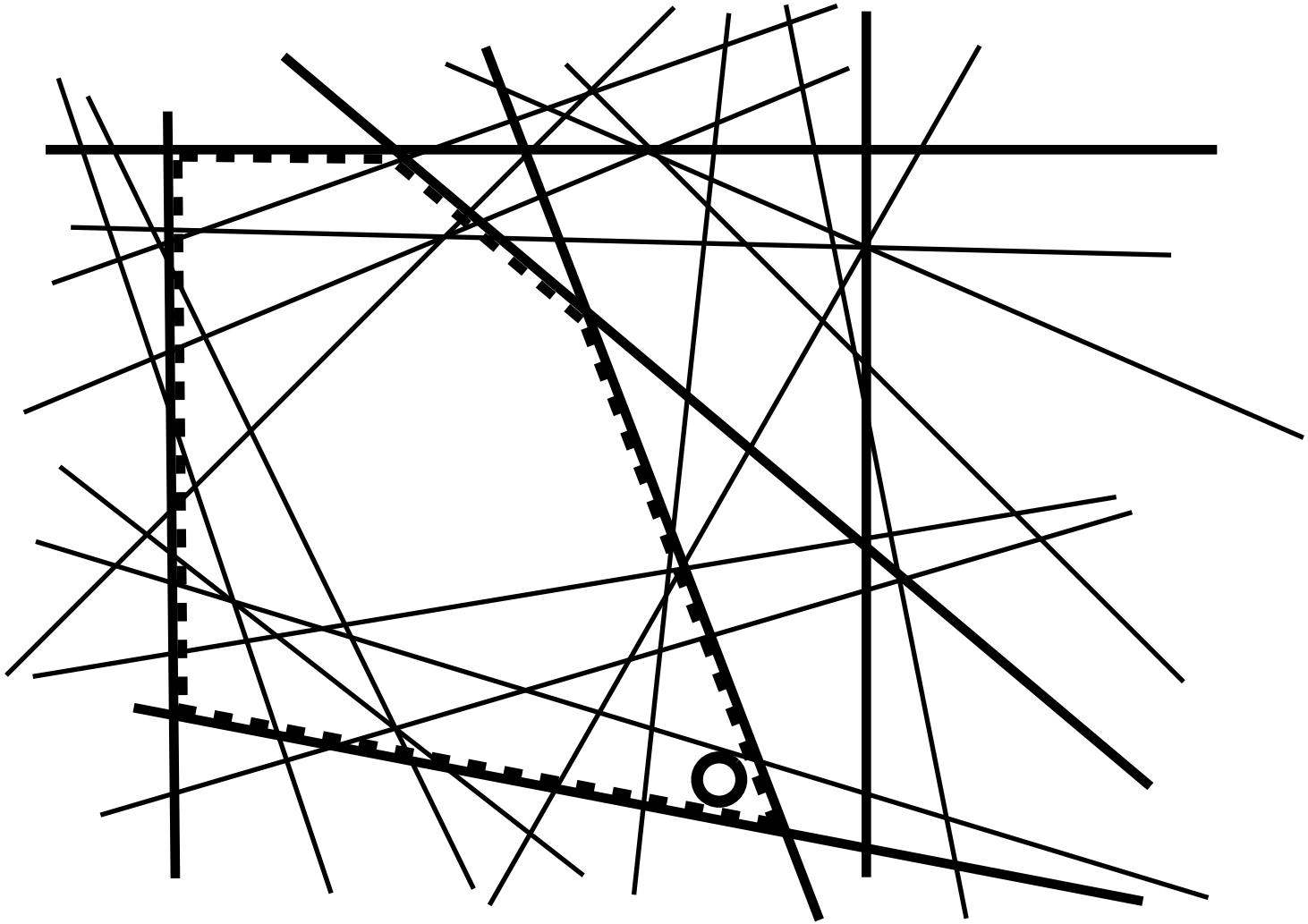


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Berkeley NLP

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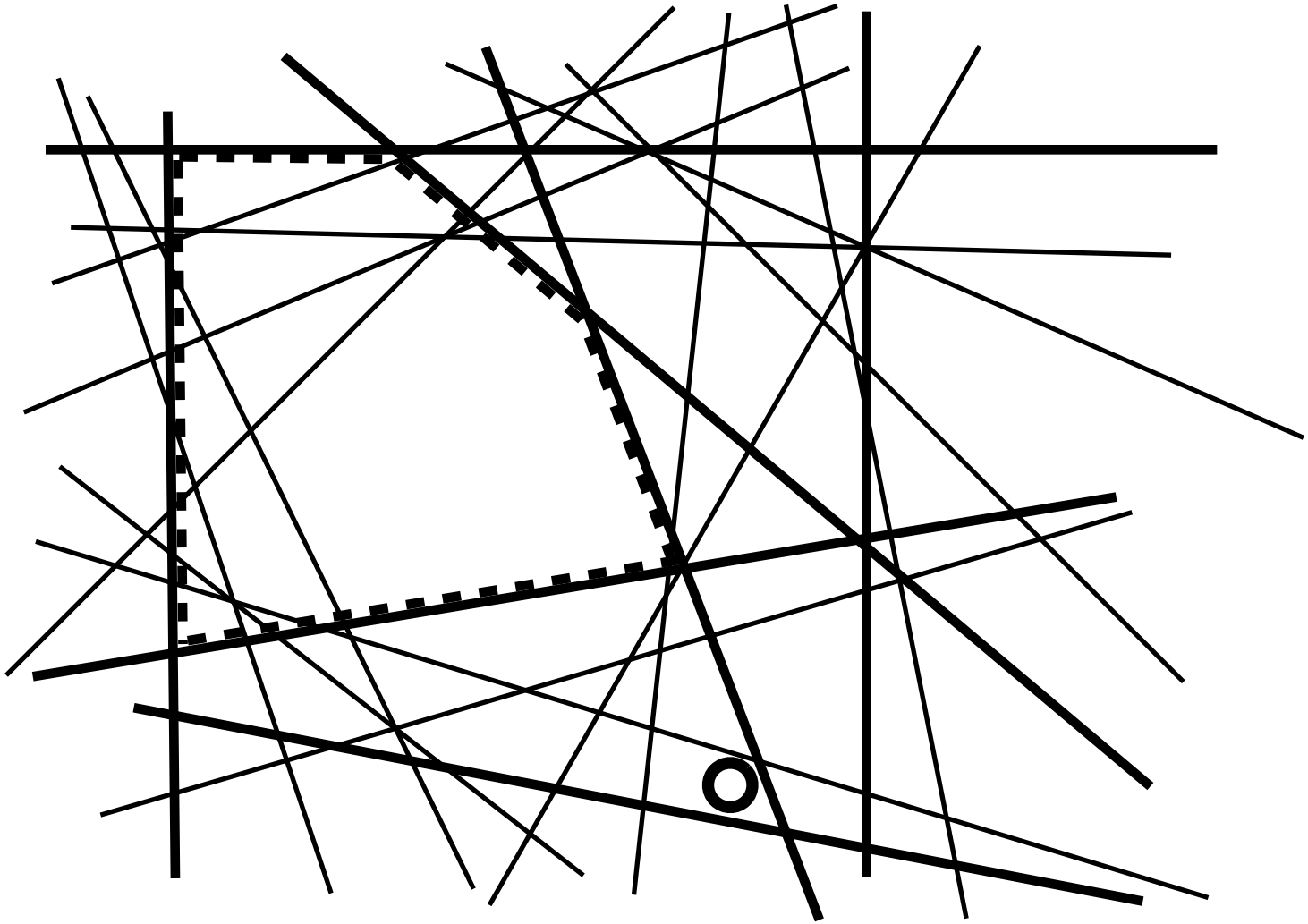

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Berkeley NLP

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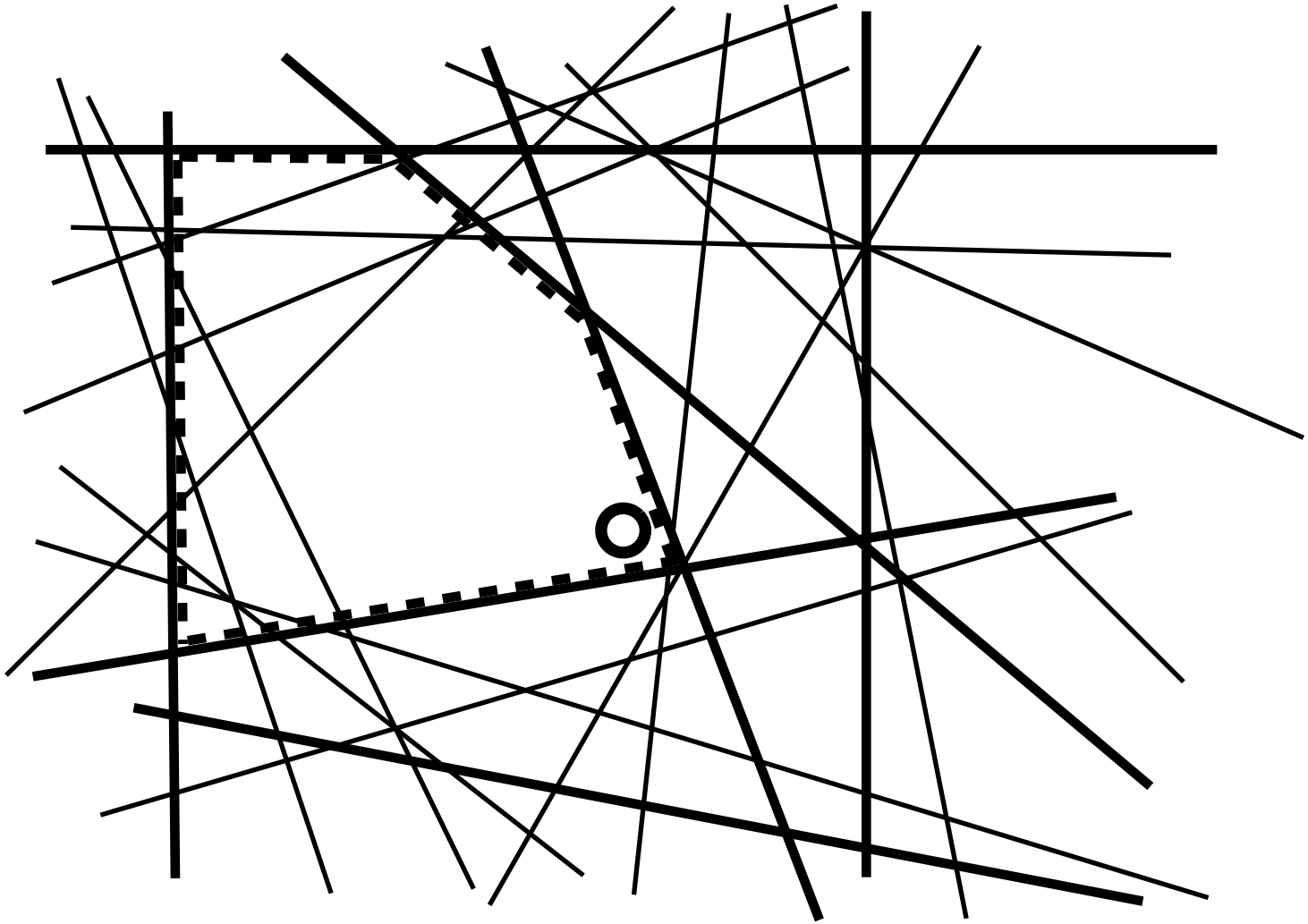

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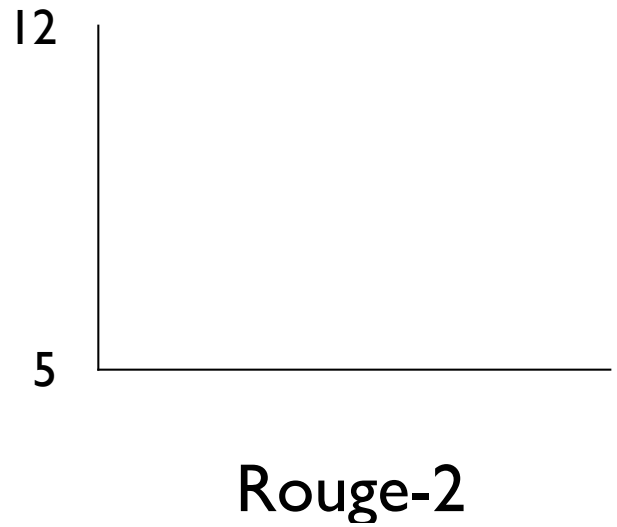
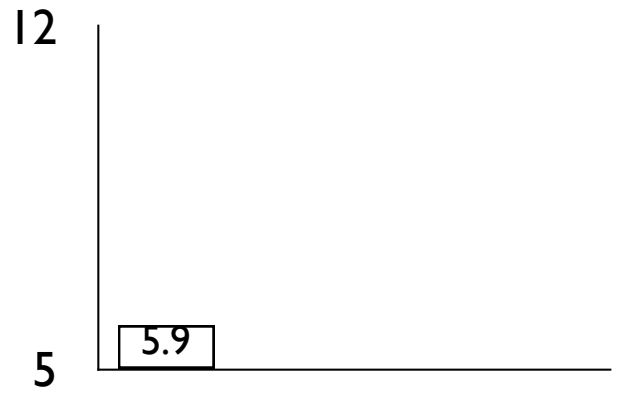
Berkeley NLP

# Results



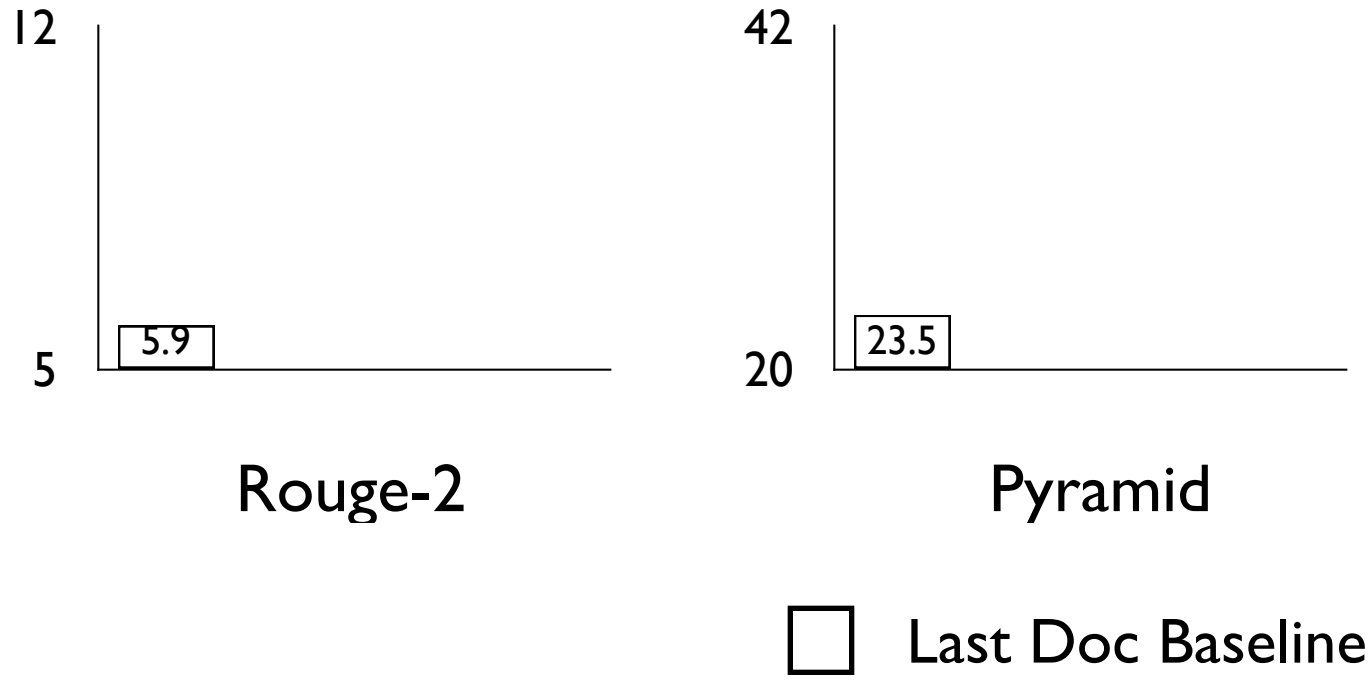
# Results



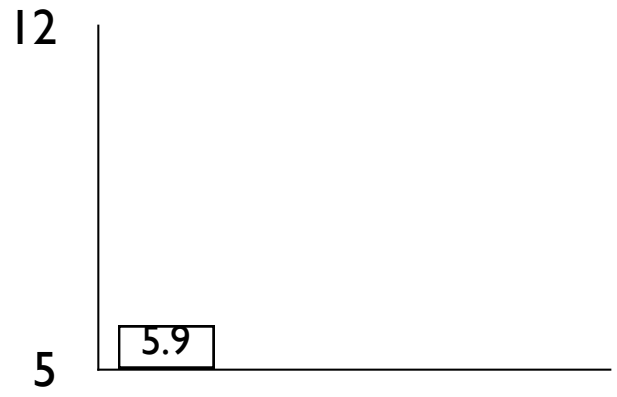

Rouge-2

Last Doc Baseline

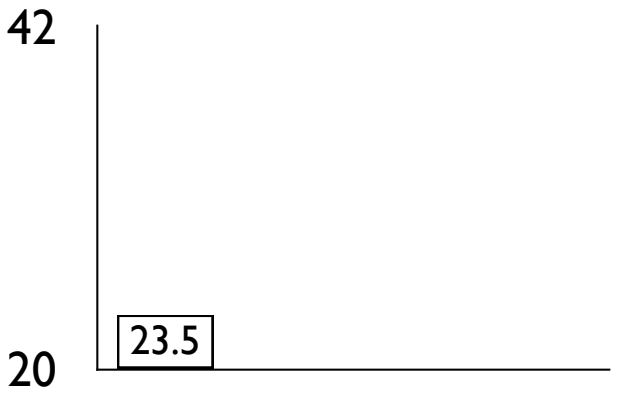
# Results



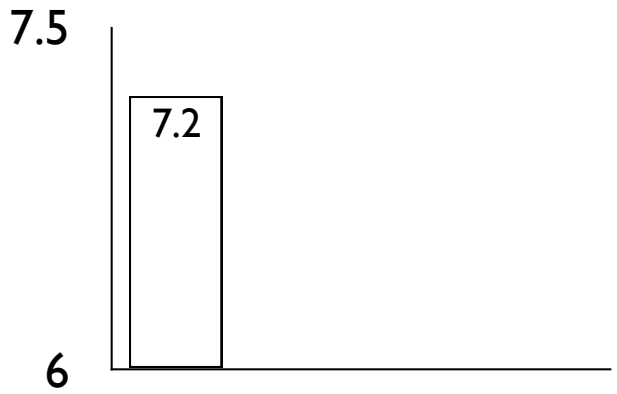
# Results




Rouge-2



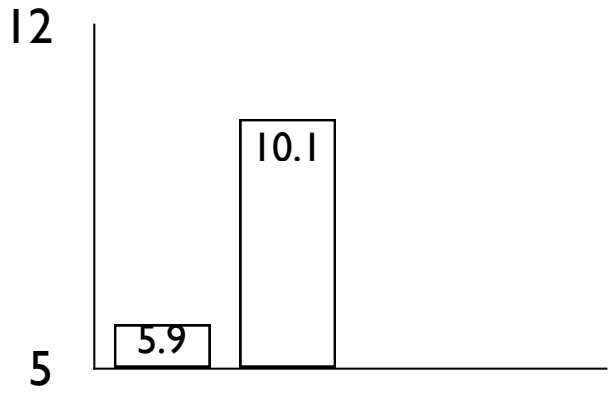

Pyramid



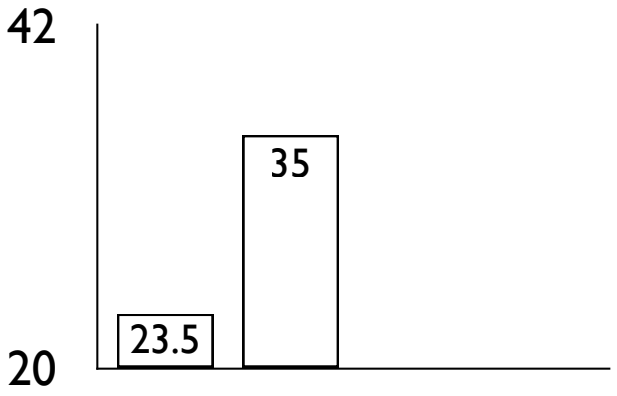

Linguistic Quality

Last Doc Baseline

# Results




Rouge-2

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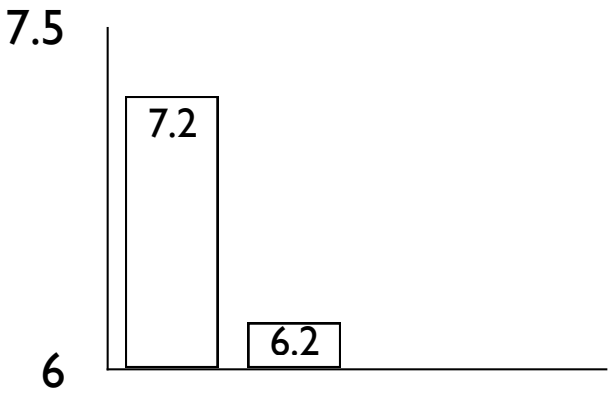
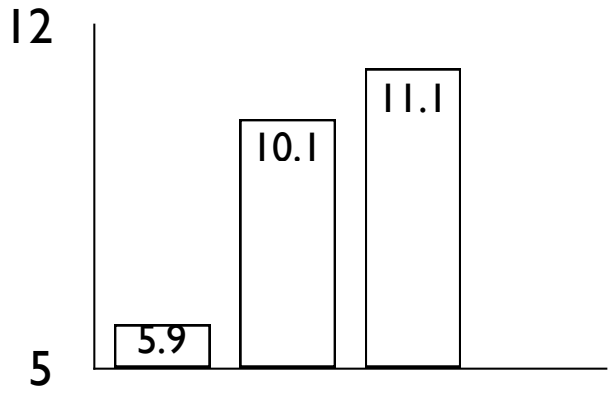



Linguistic Quality

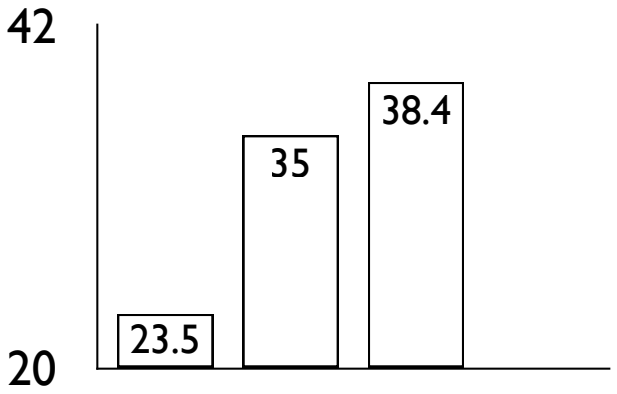
Last Doc Baseline

Extractive Baseline

# Results




Rouge-2

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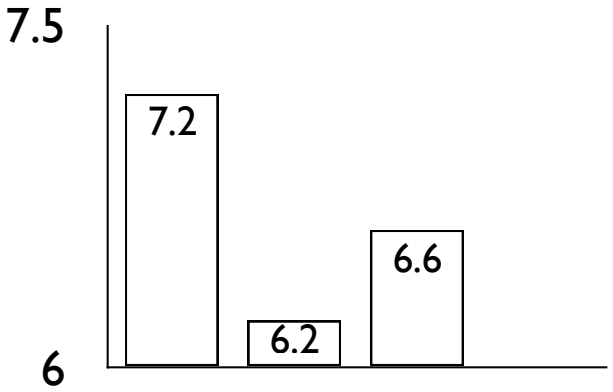


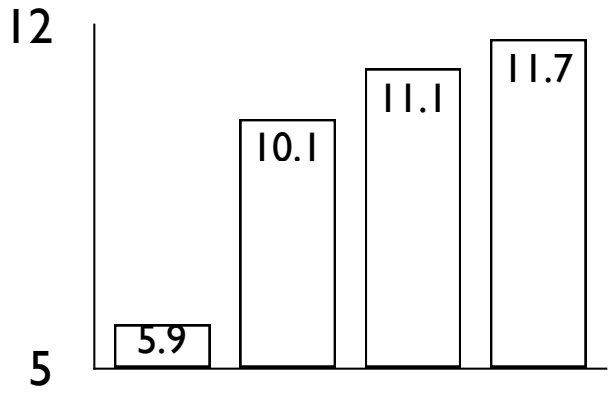

Linguistic Quality

Last Doc Baseline

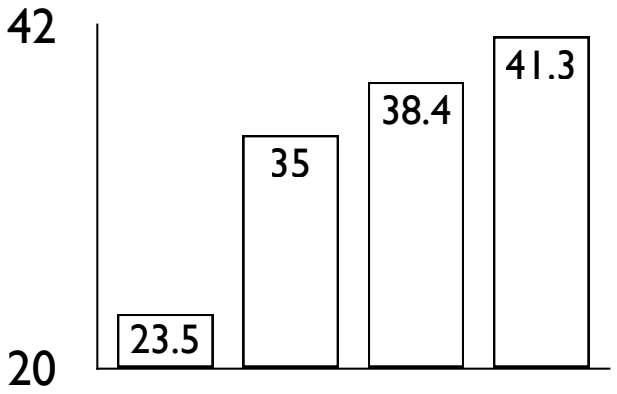
Extractive Baseline

Learned Extractive

# Results




Rouge-2

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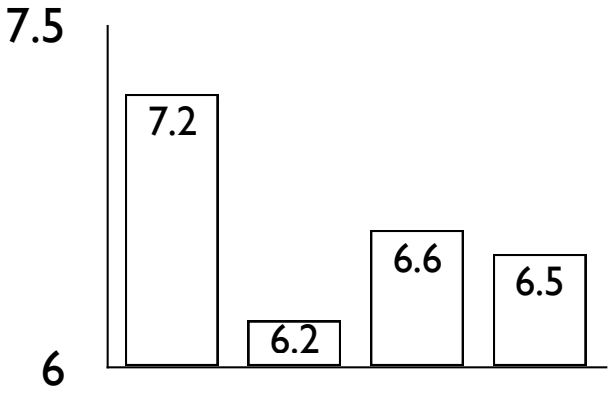


Linguistic Quality

- Last Doc Baseline
- Extractive Baseline
- Learned Extractive
- Learned E + C

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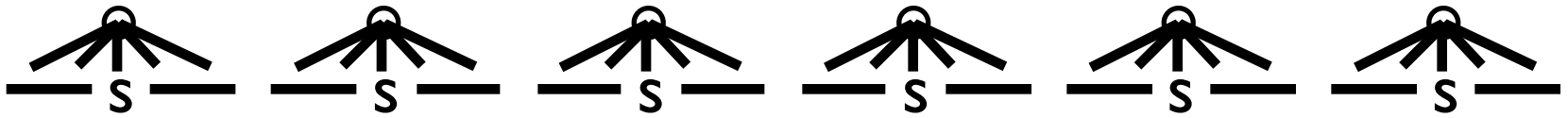
# Coarse-to-fine Decoding



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N L P

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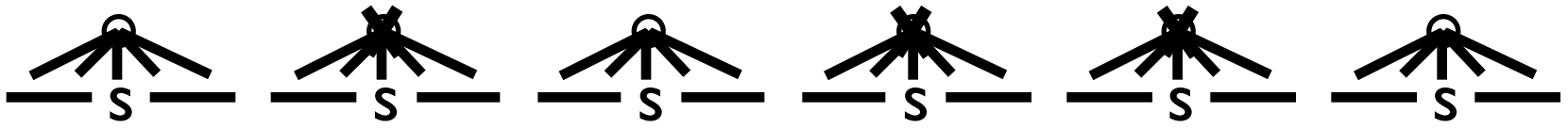

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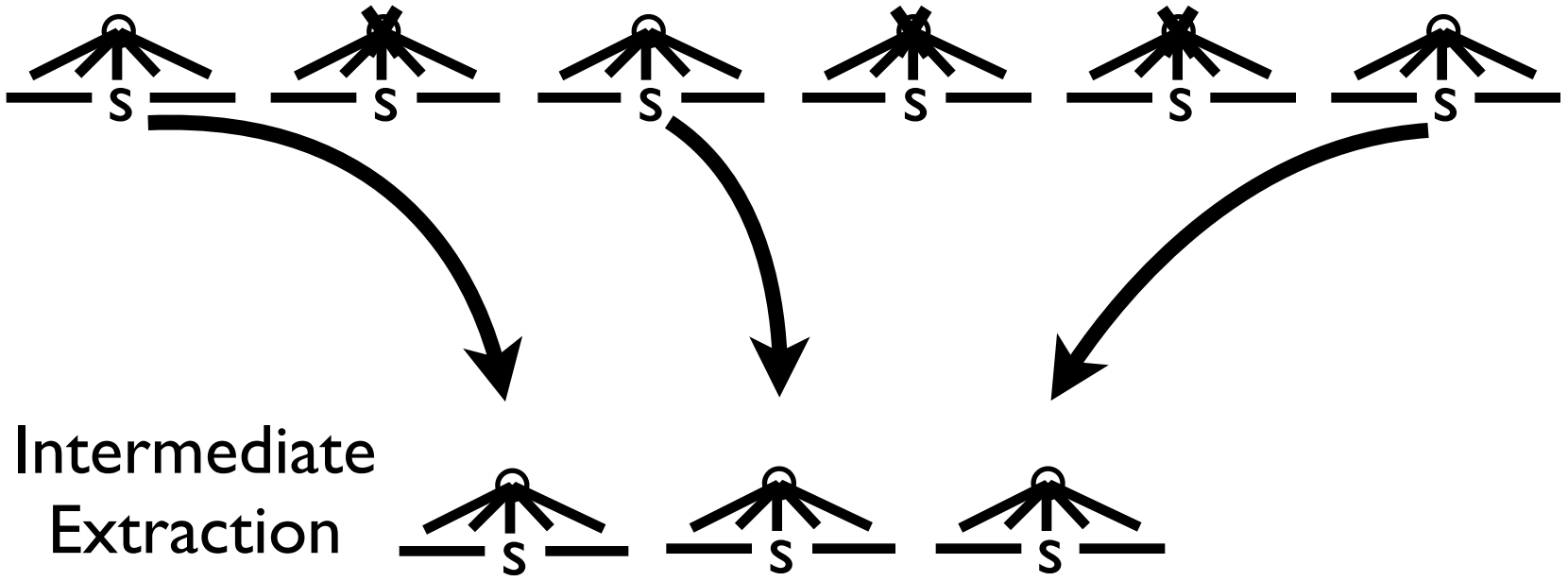

Berkeley NLP

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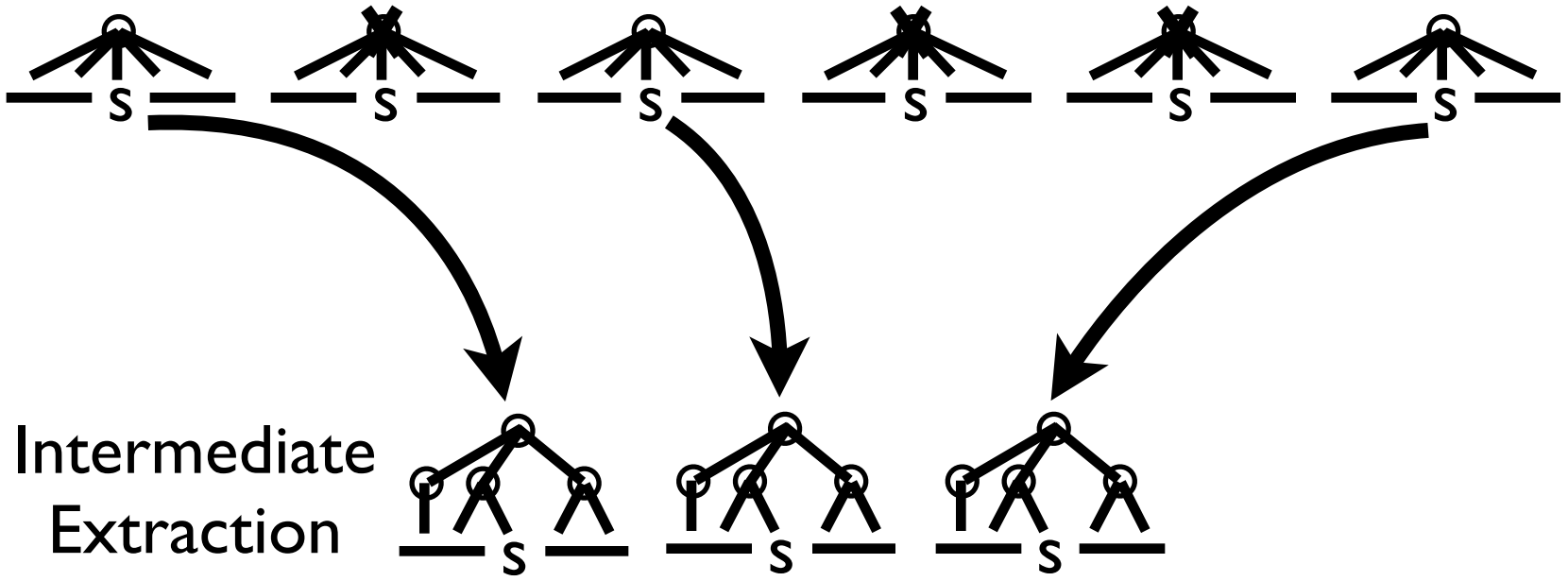

Berkeley NLP

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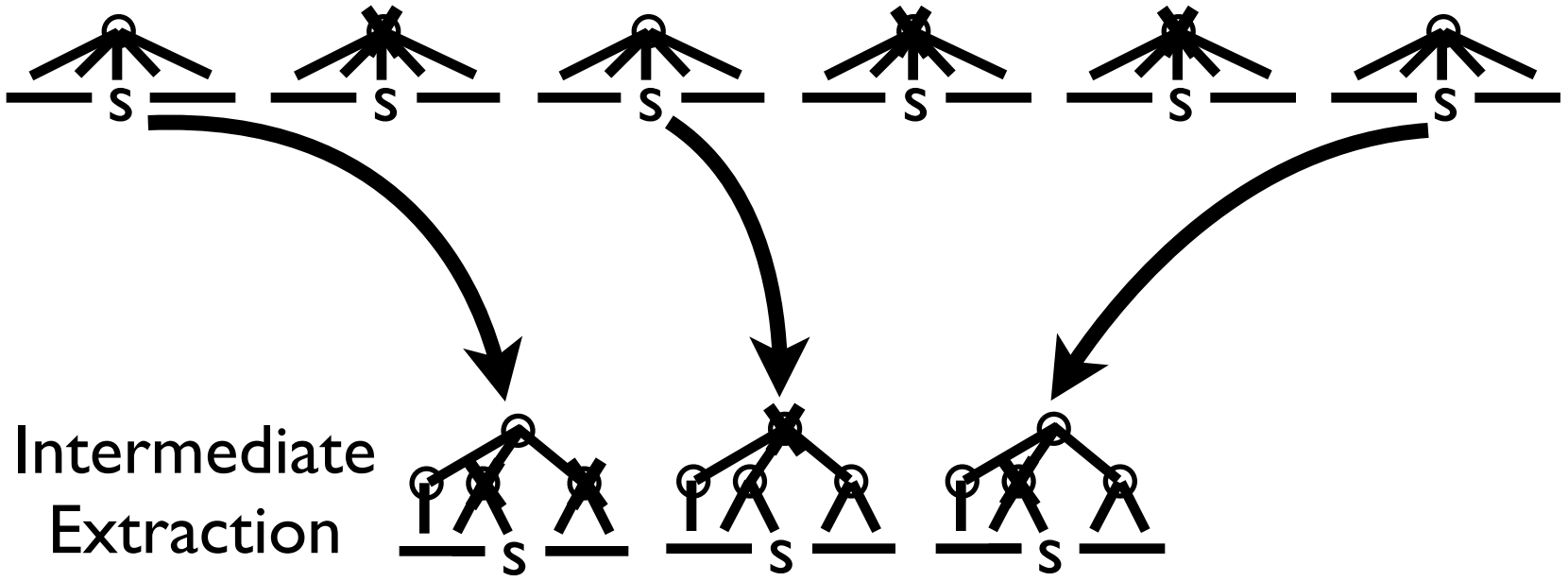

Berkeley NLP

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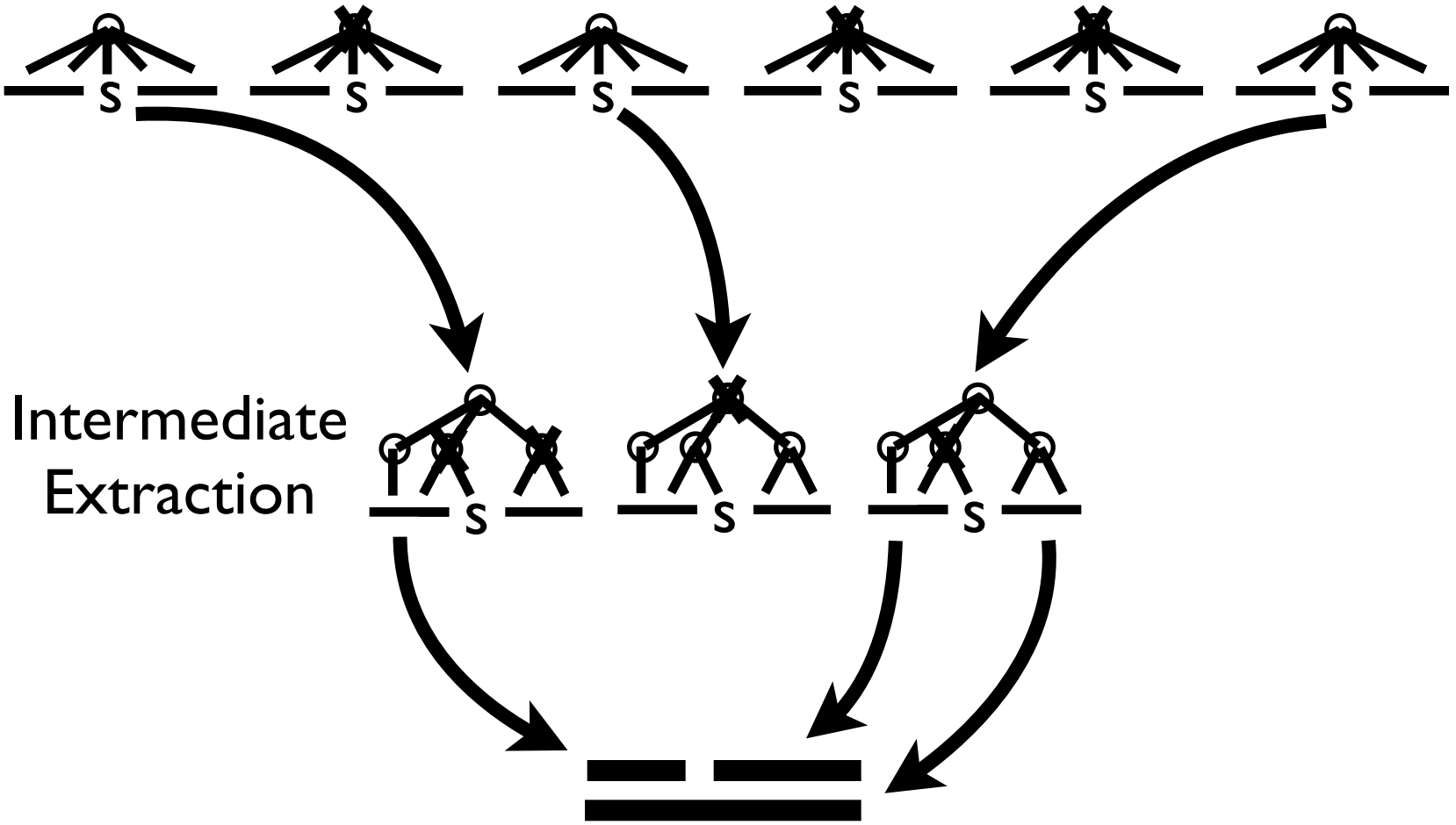

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N L P

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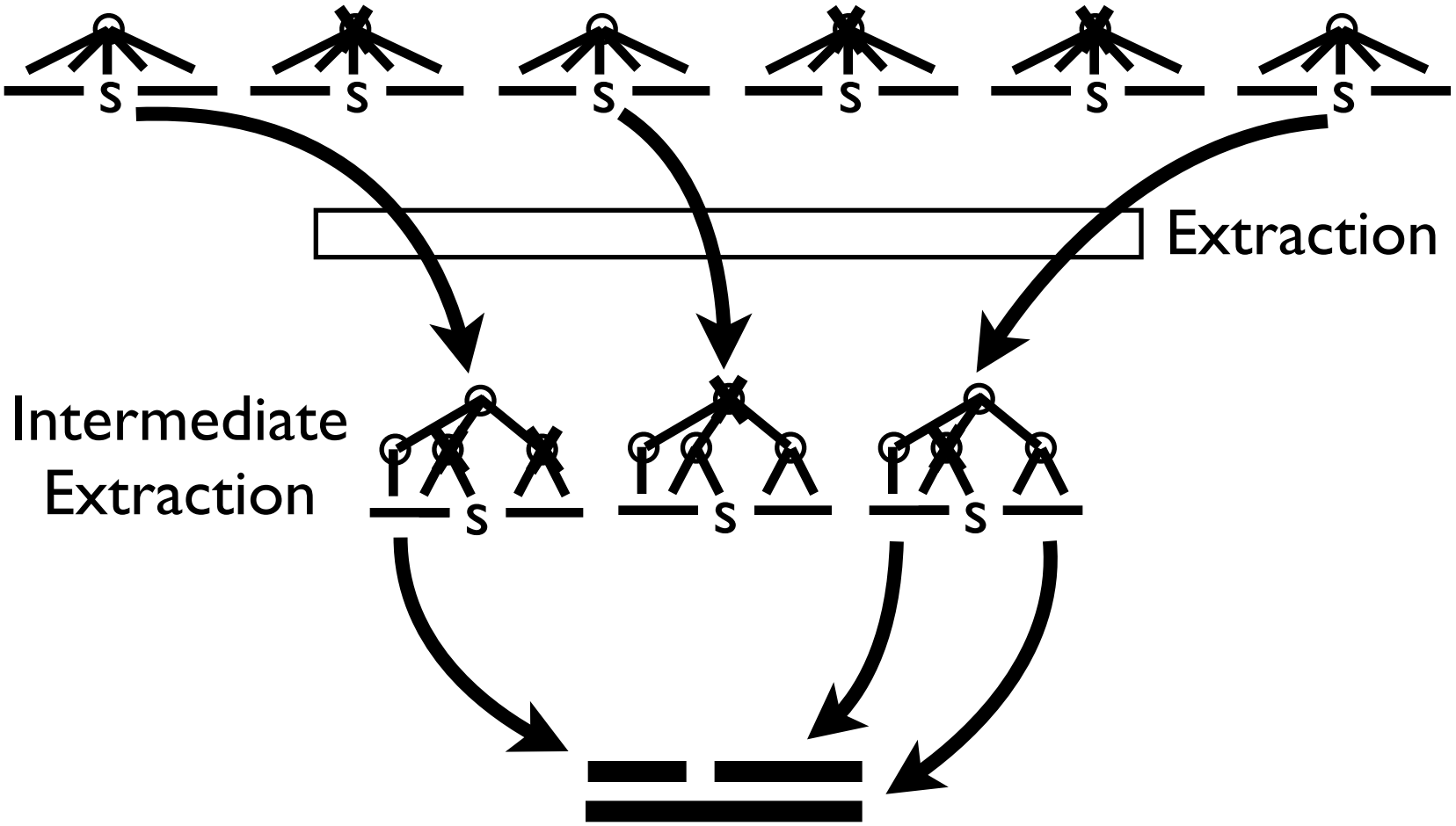

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N L P

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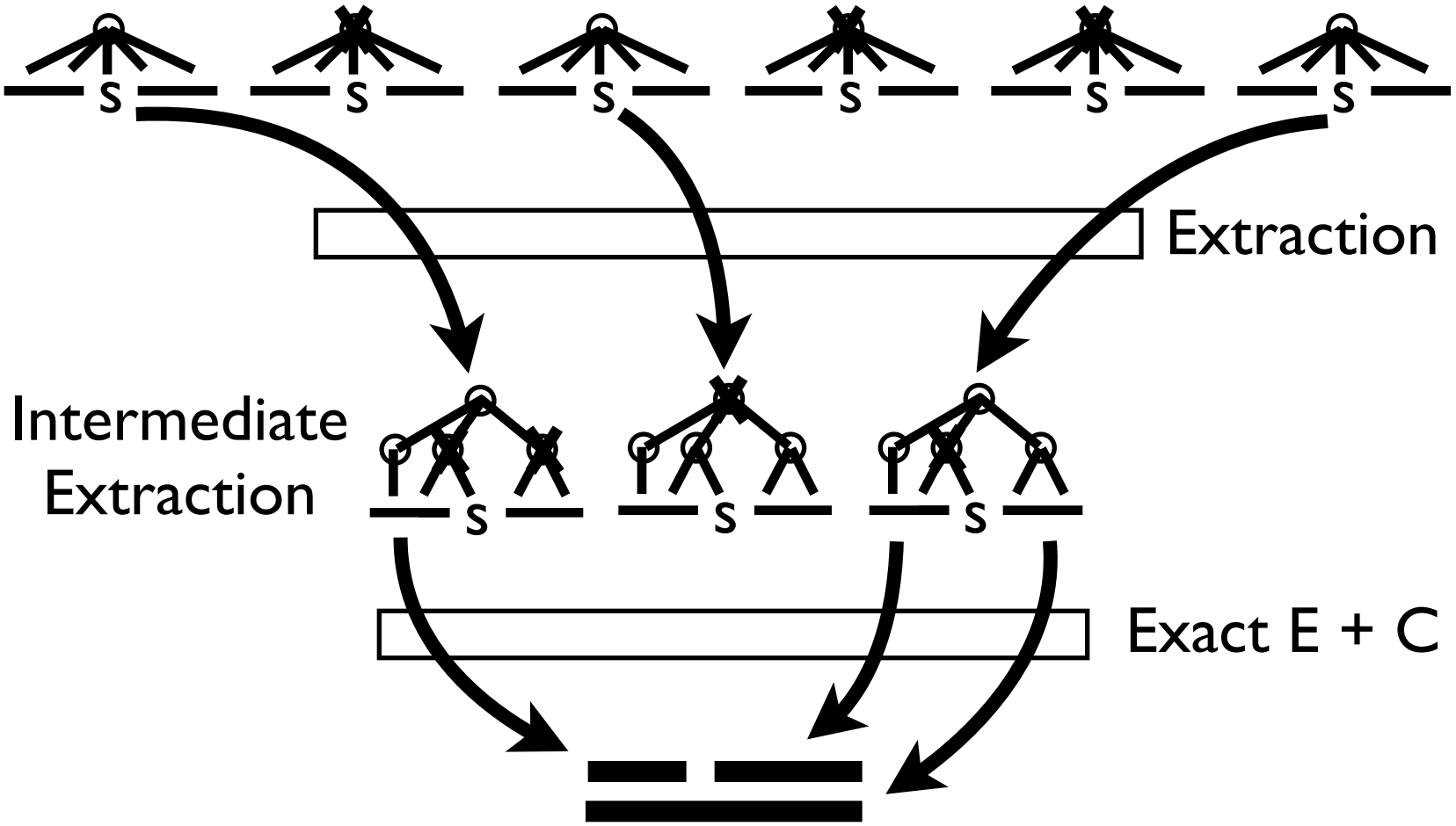

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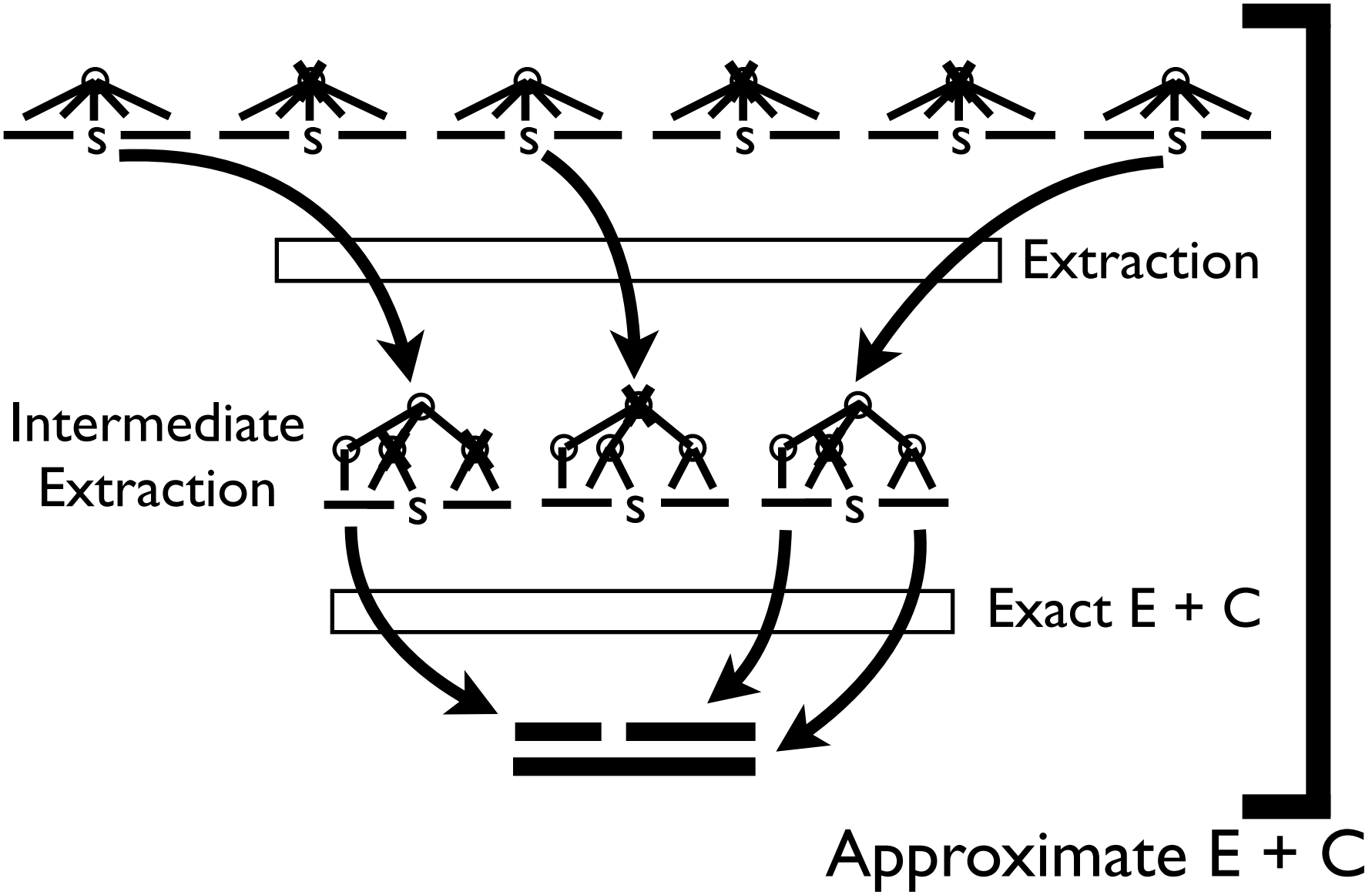

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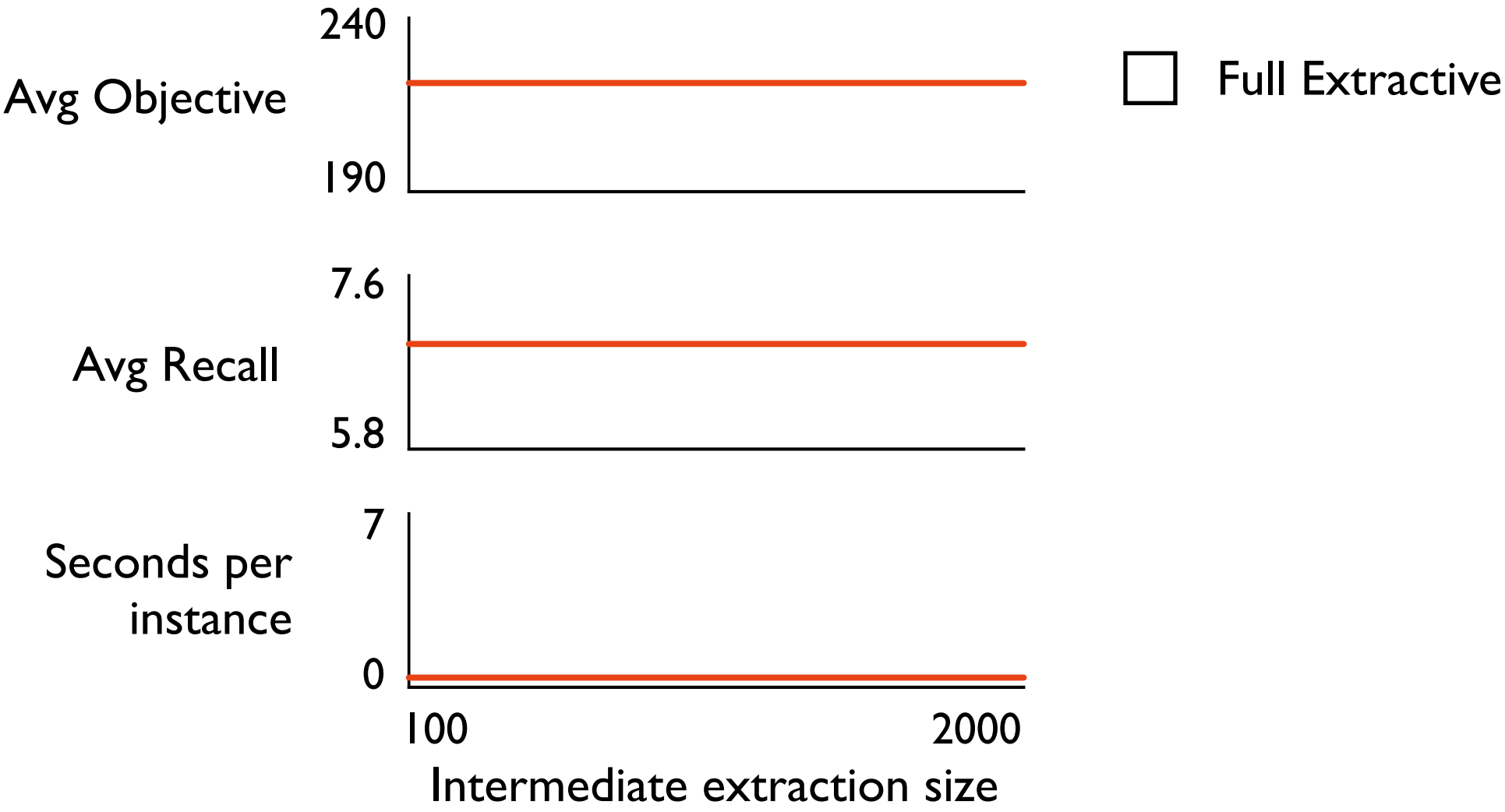

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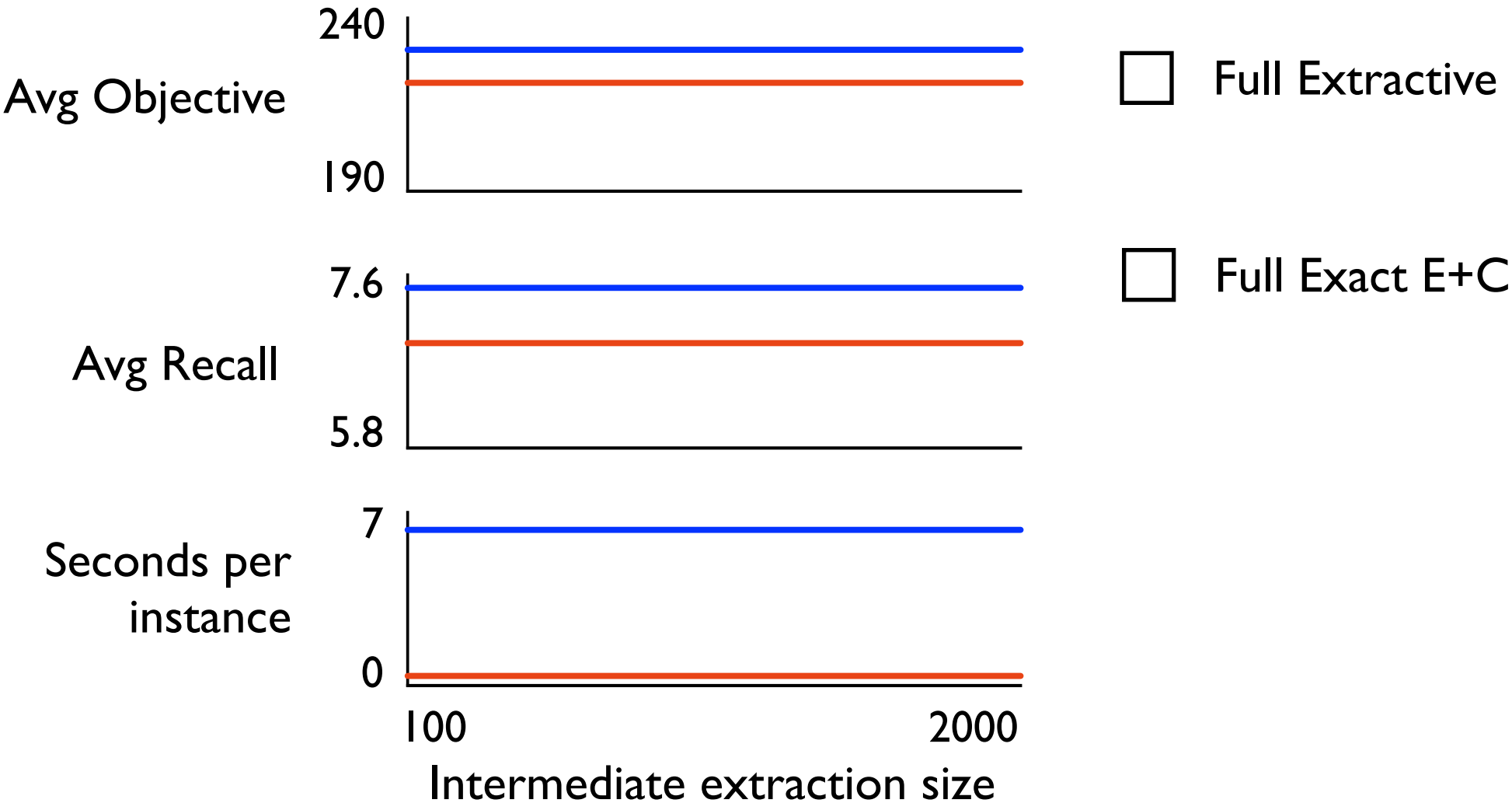

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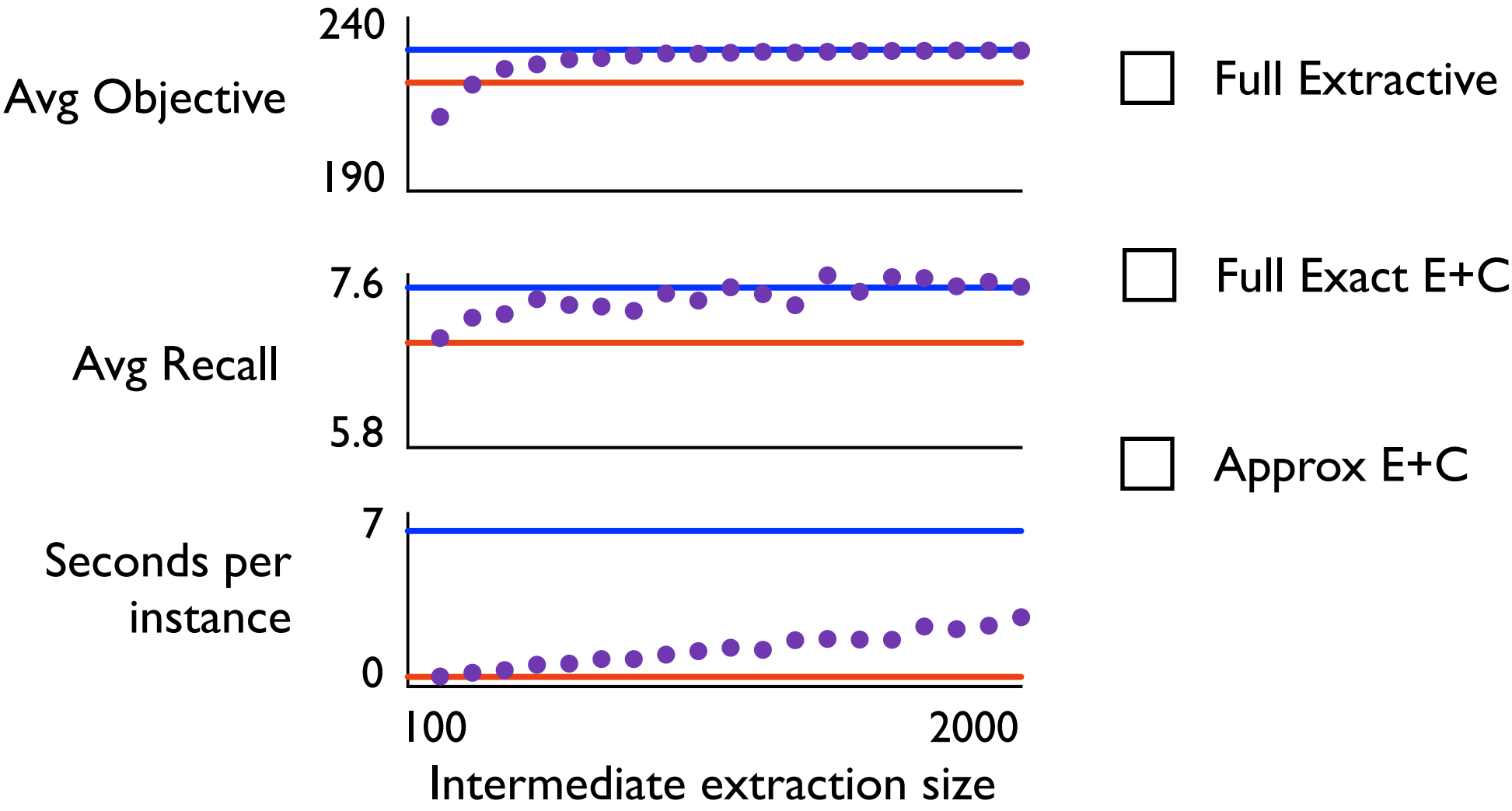

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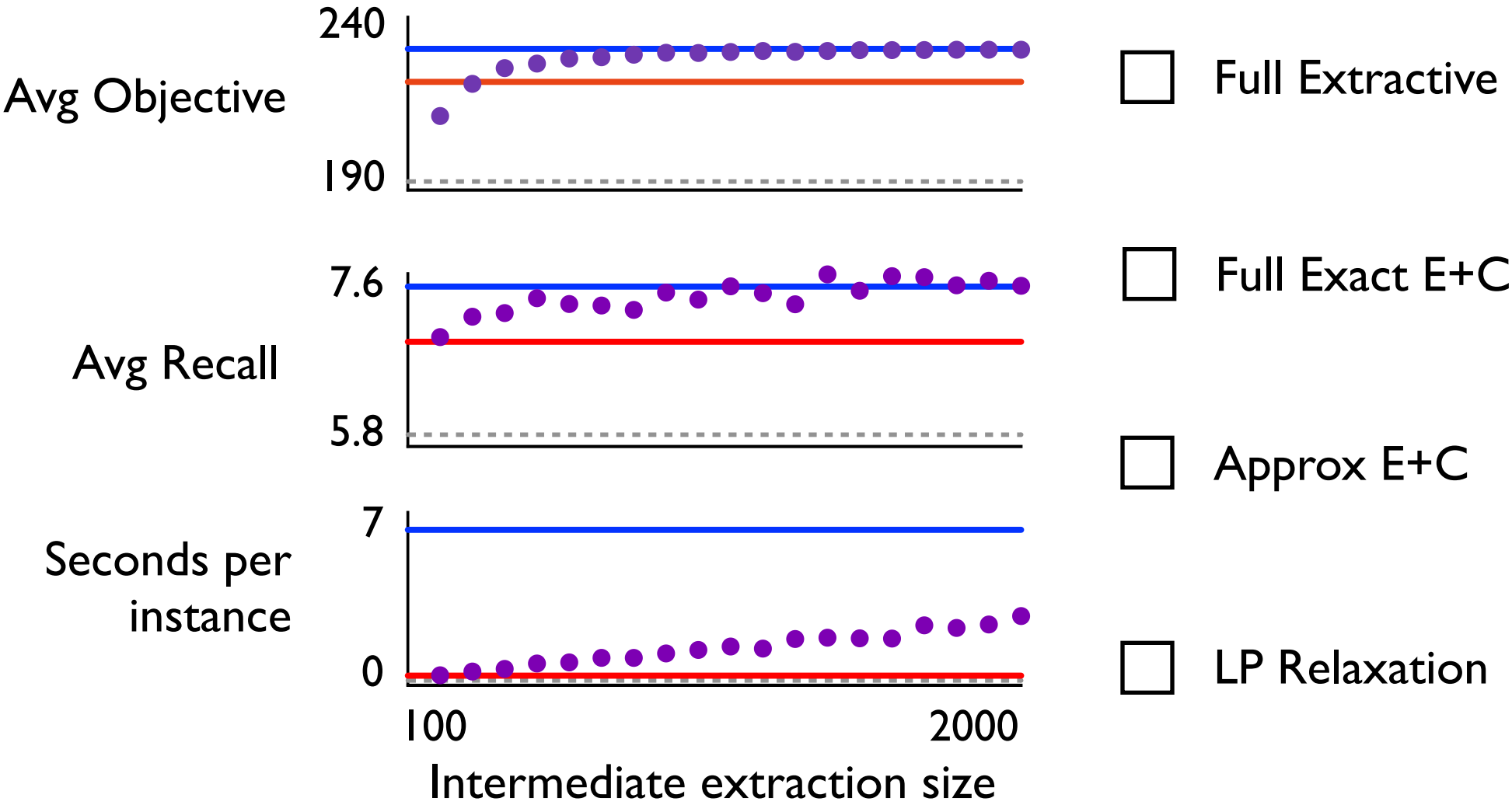


# Piano Music Transcription

Berkeley NLP

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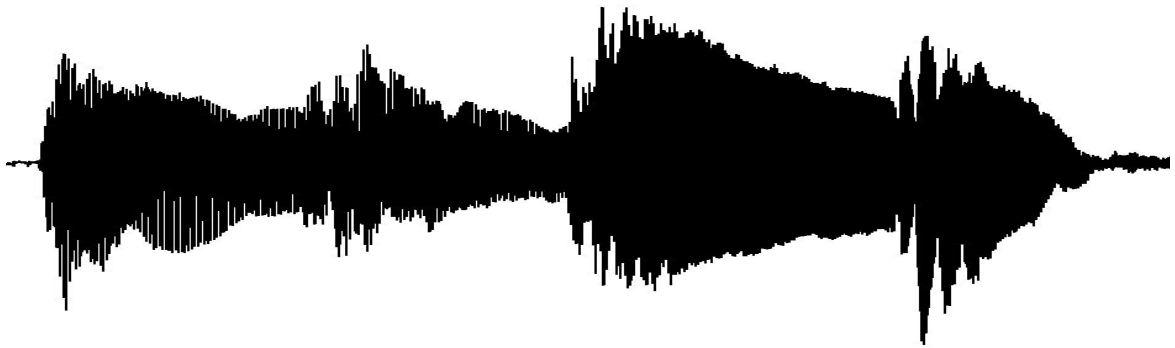

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N L P

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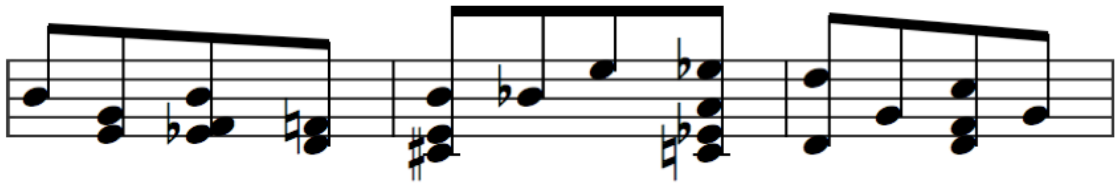

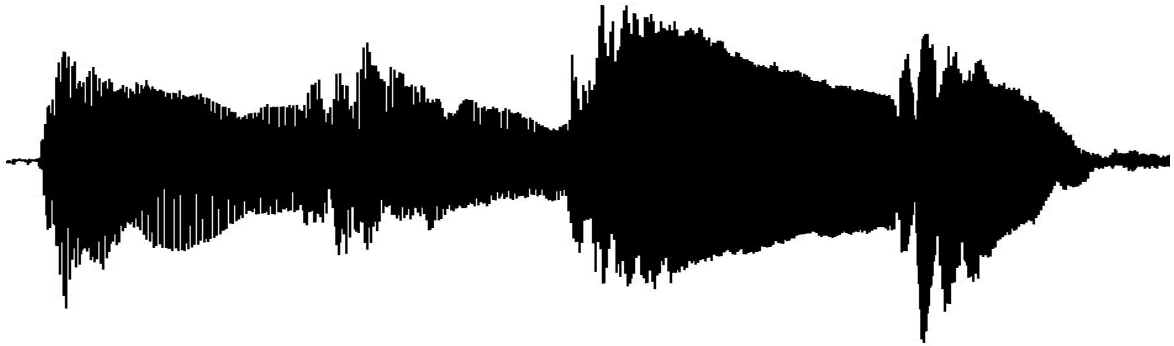

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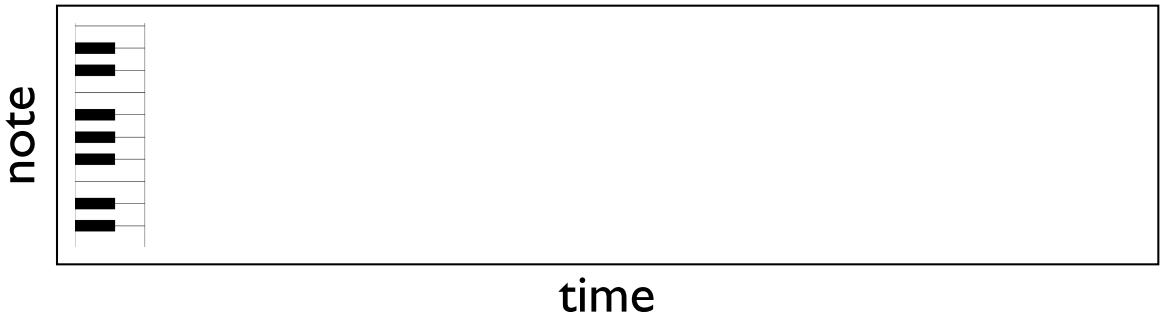
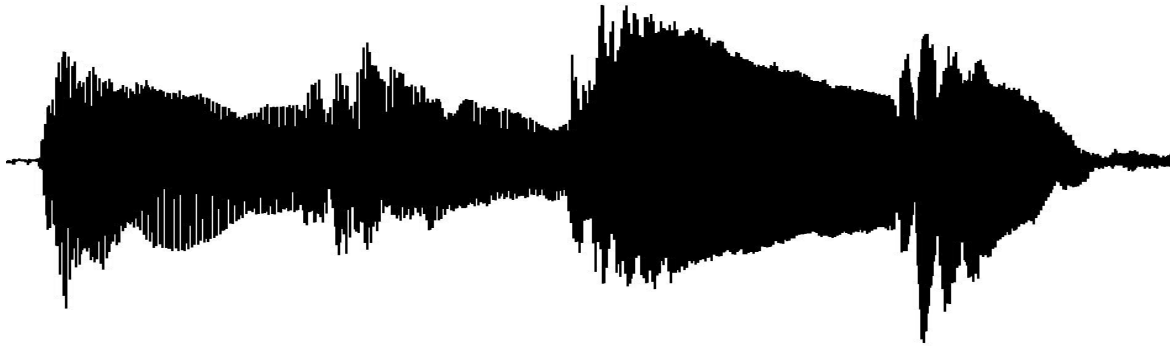
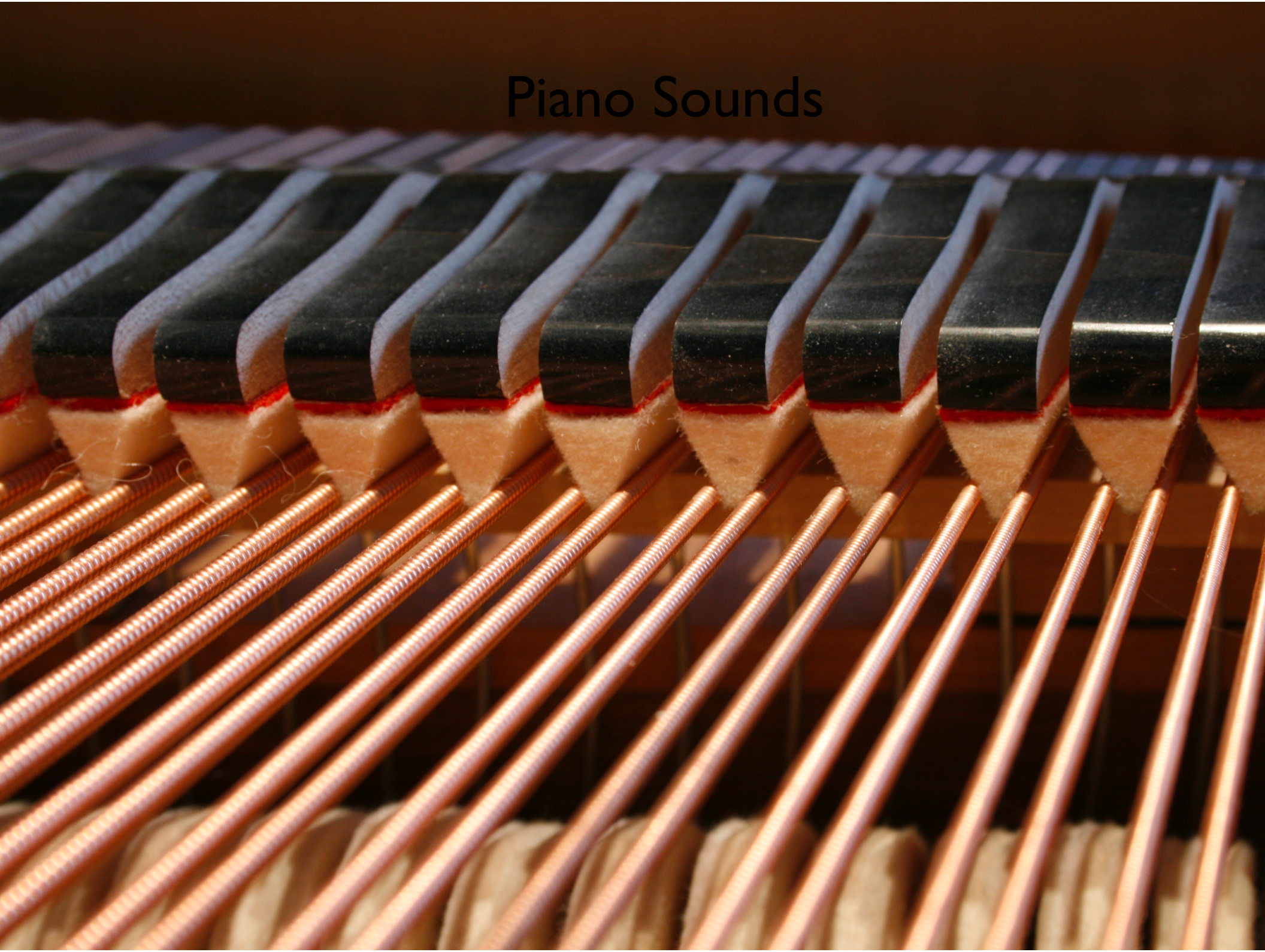


# Piano Sounds



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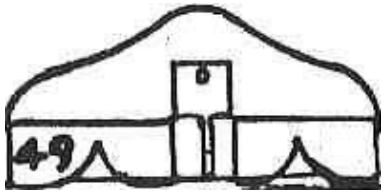


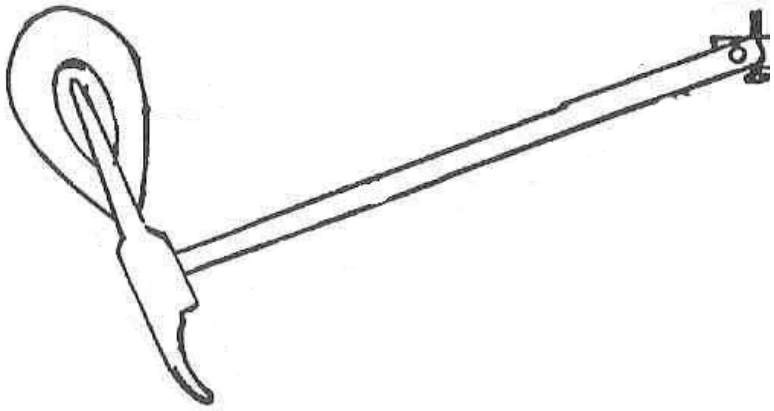

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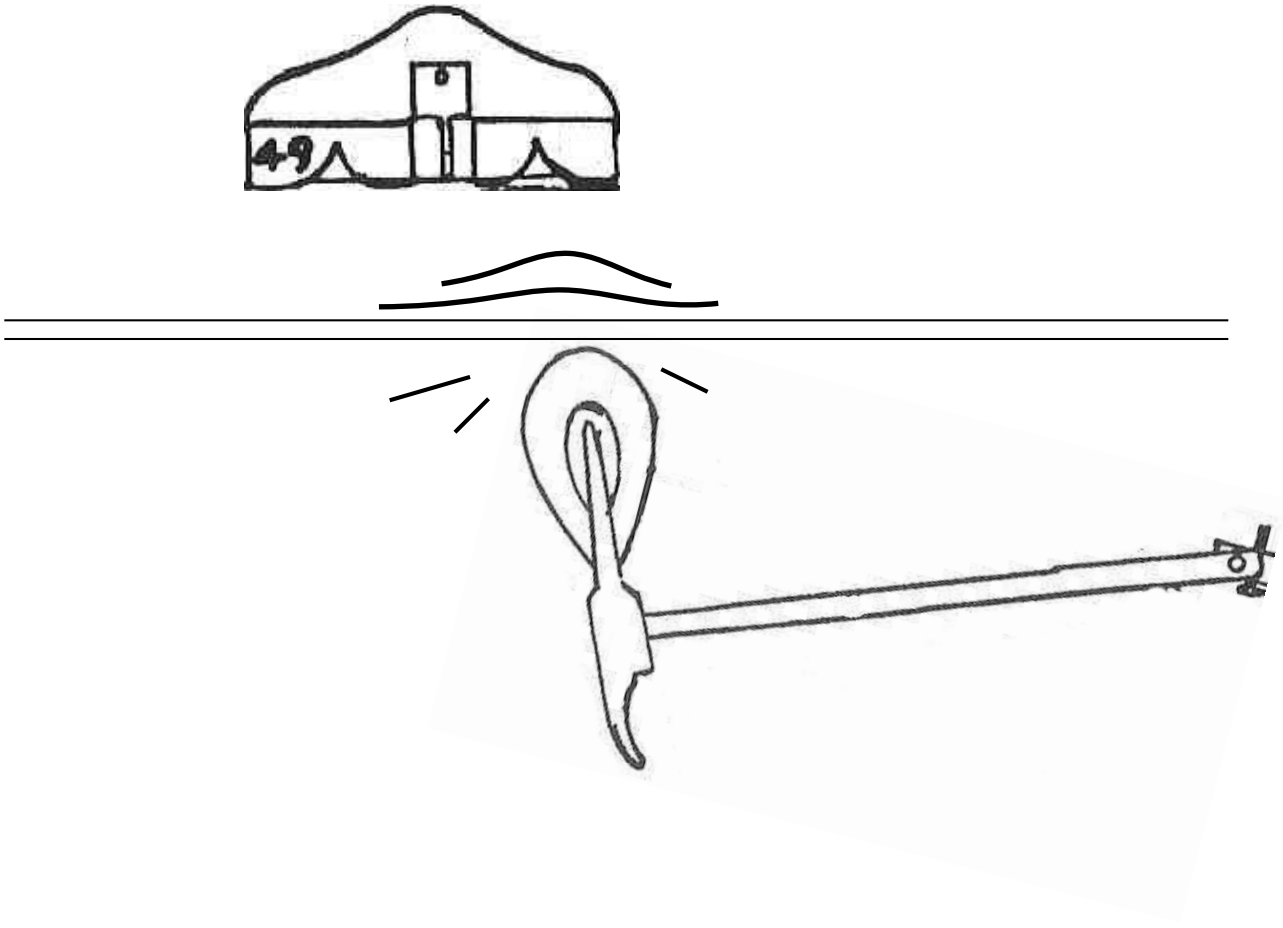

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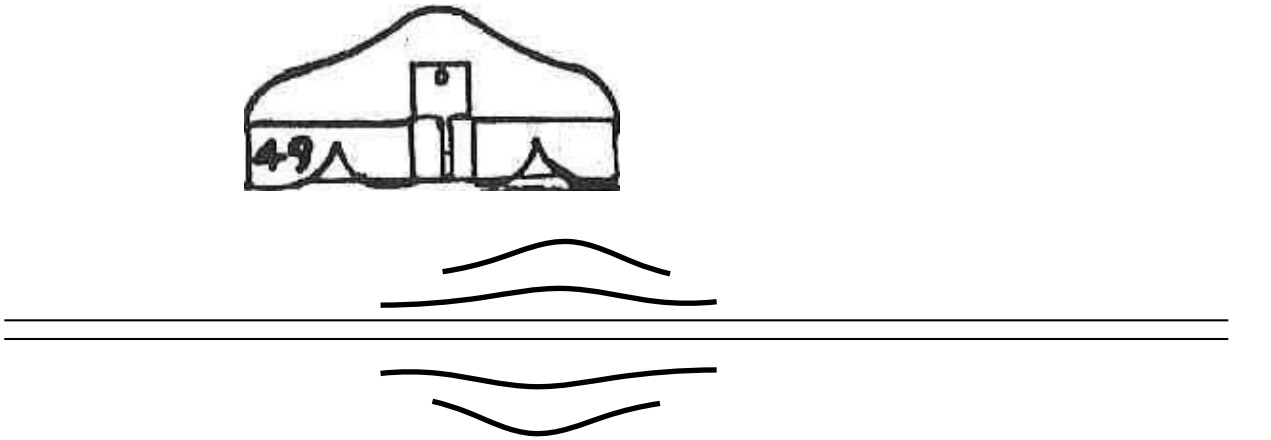
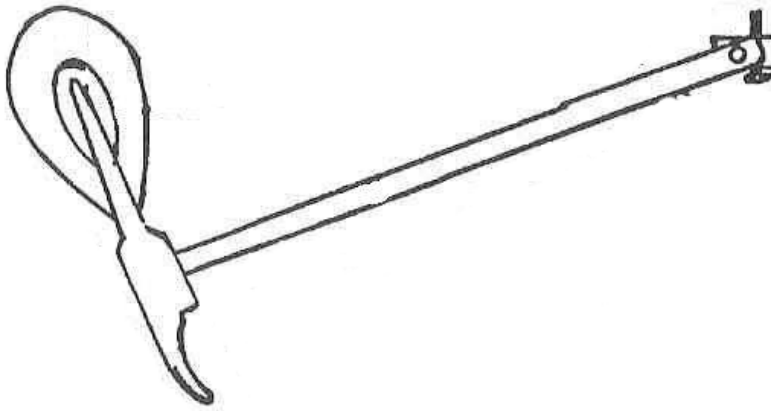
N L P

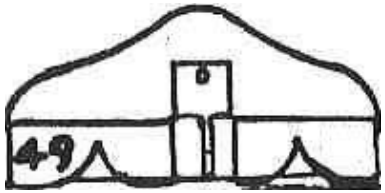
# Piano Sounds

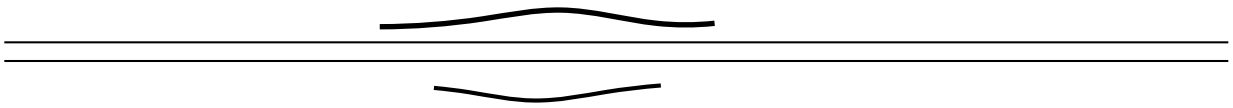


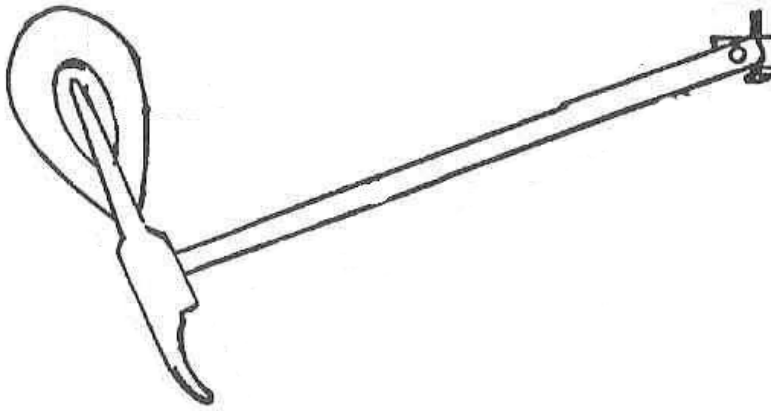



Berkeley
N L P

# Piano Sounds

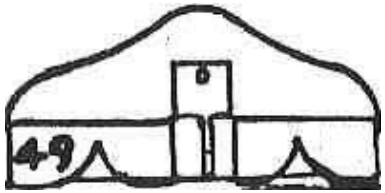


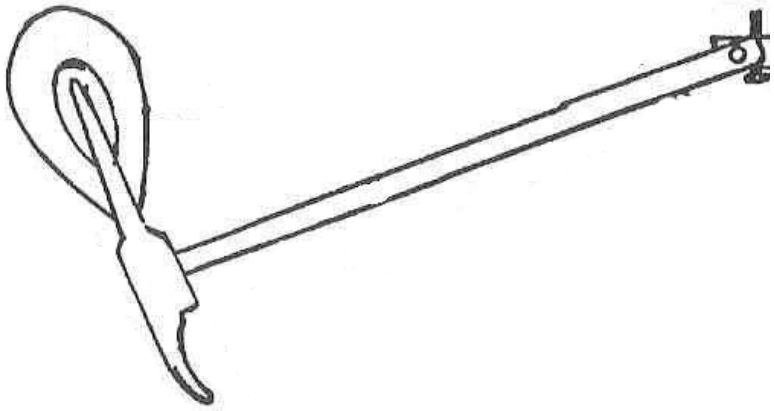





Berkeley
N L P

# Piano Sounds

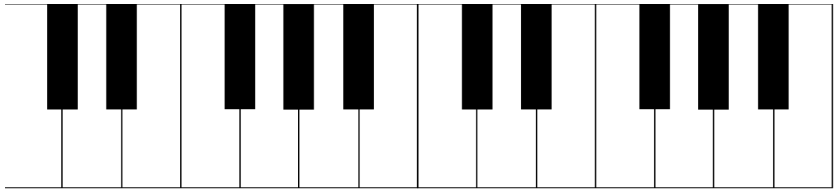


Berkeley

N L P

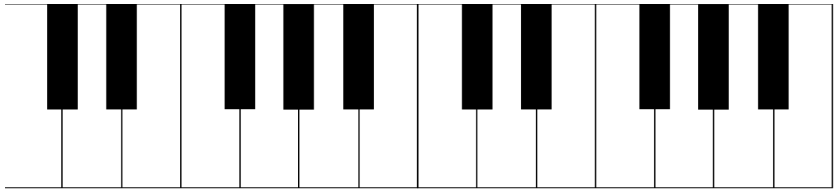
# Piano Sounds



Berkeley

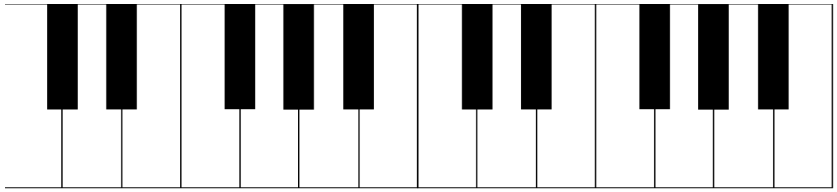
N L P

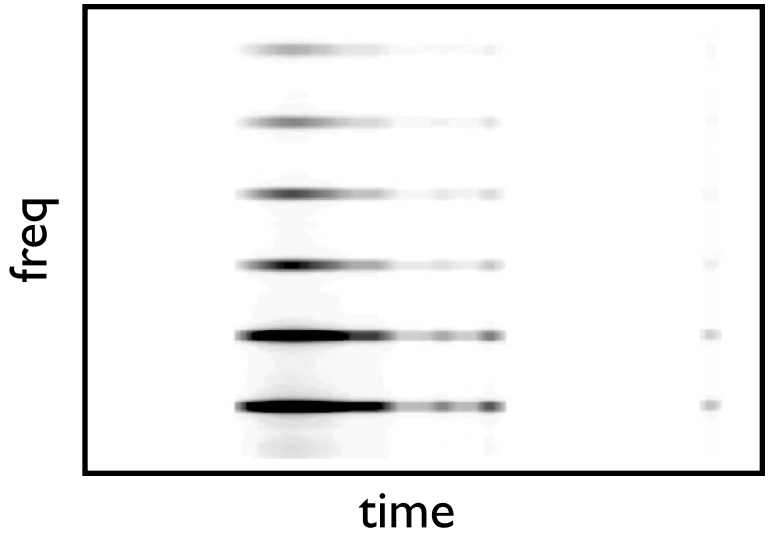
# Piano Sounds



Berkeley
N L P

# Piano Sounds





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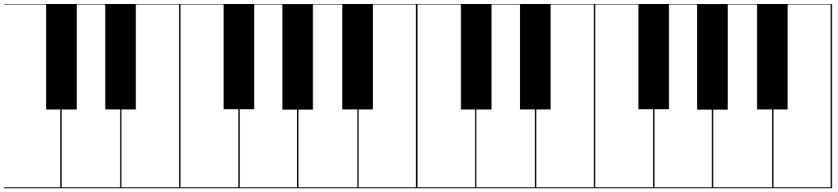
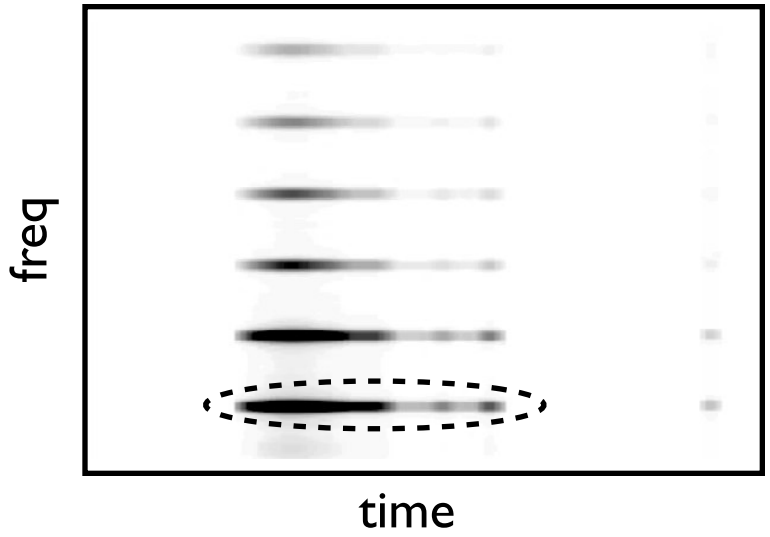
N L P

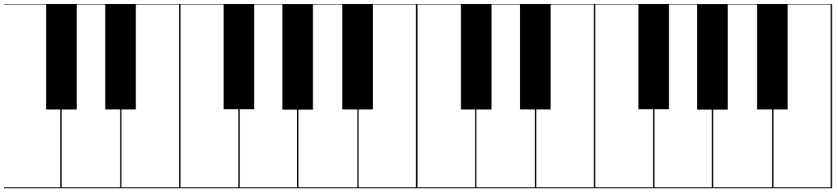
# Piano Sounds

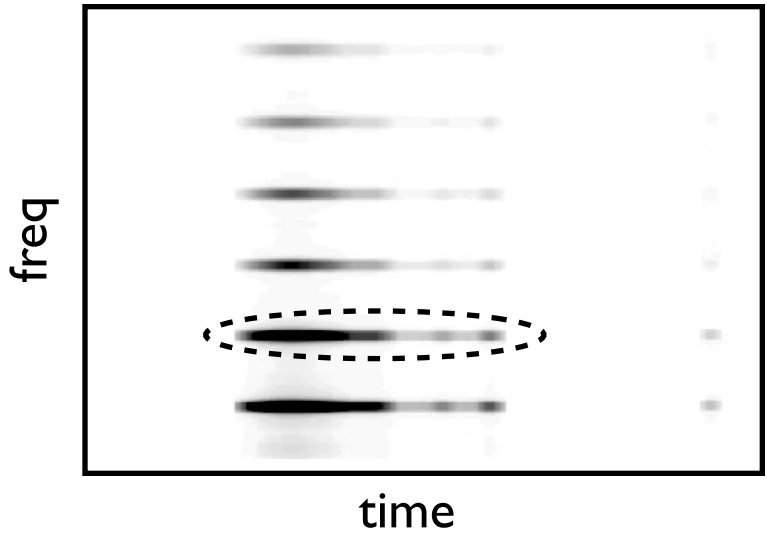




Berkeley
N L P

# Piano Sounds





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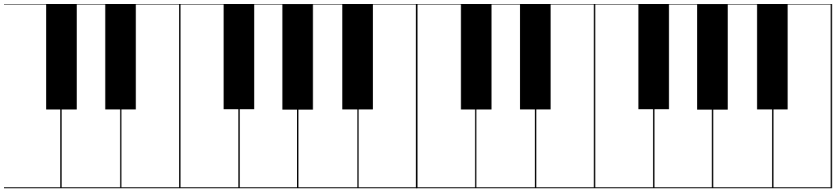
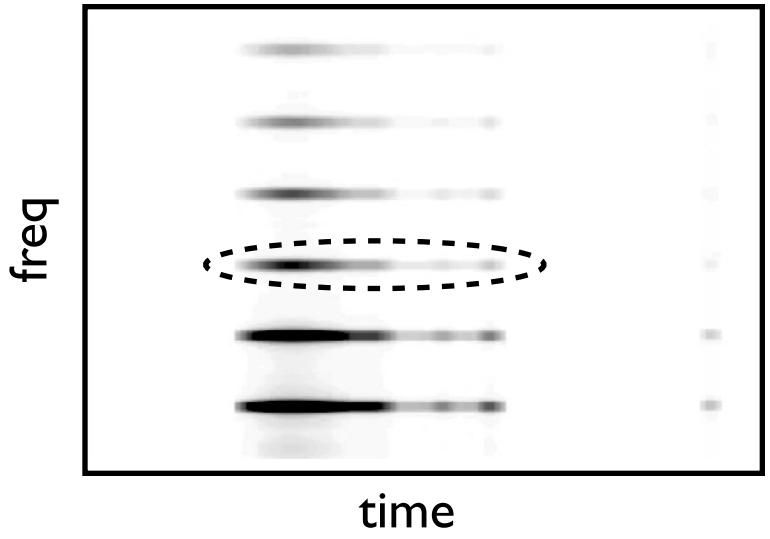
N L P

# Piano Sounds





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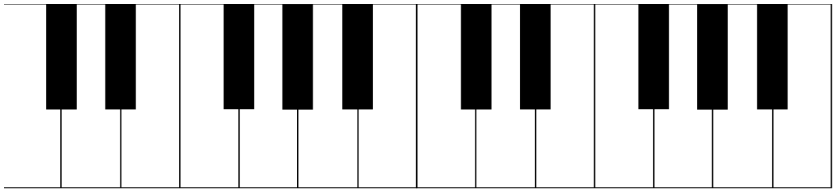
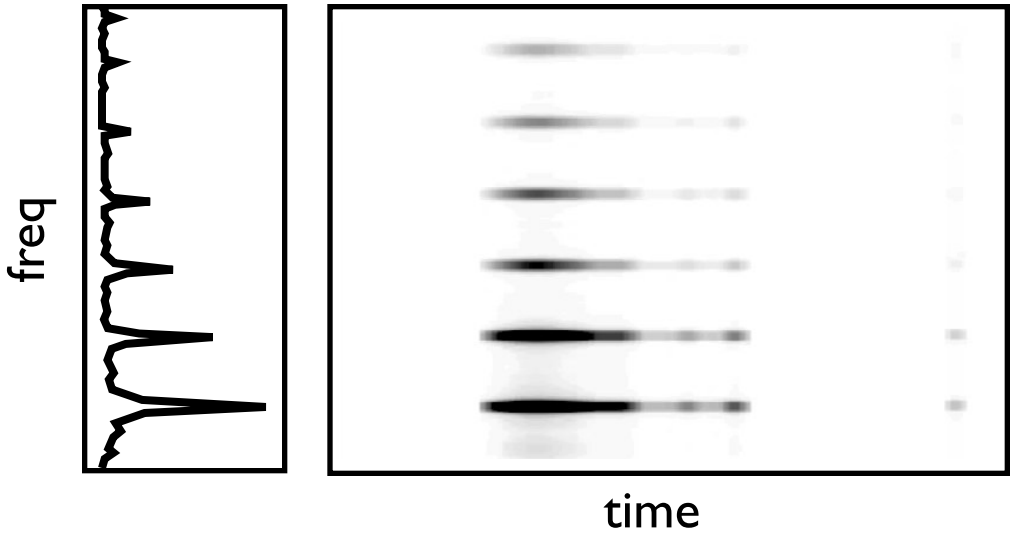
N L P

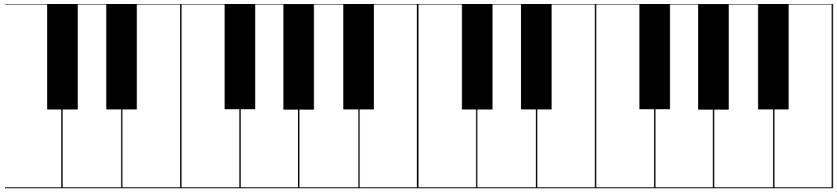
# Spectral Shape

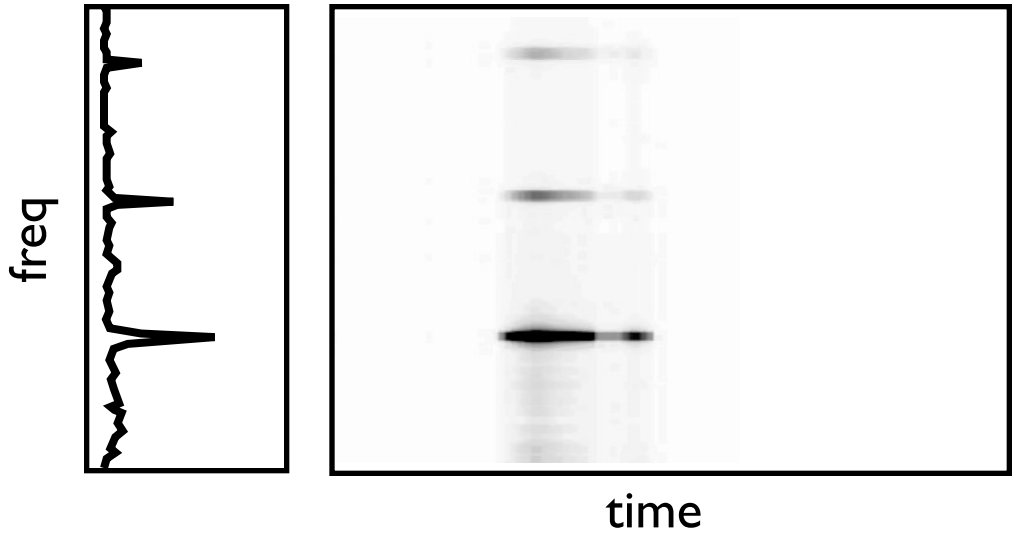




Berkeley
N L P

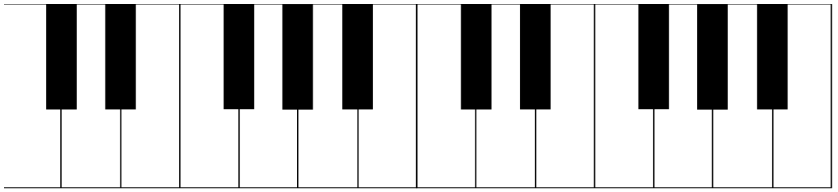
# Spectral Shape

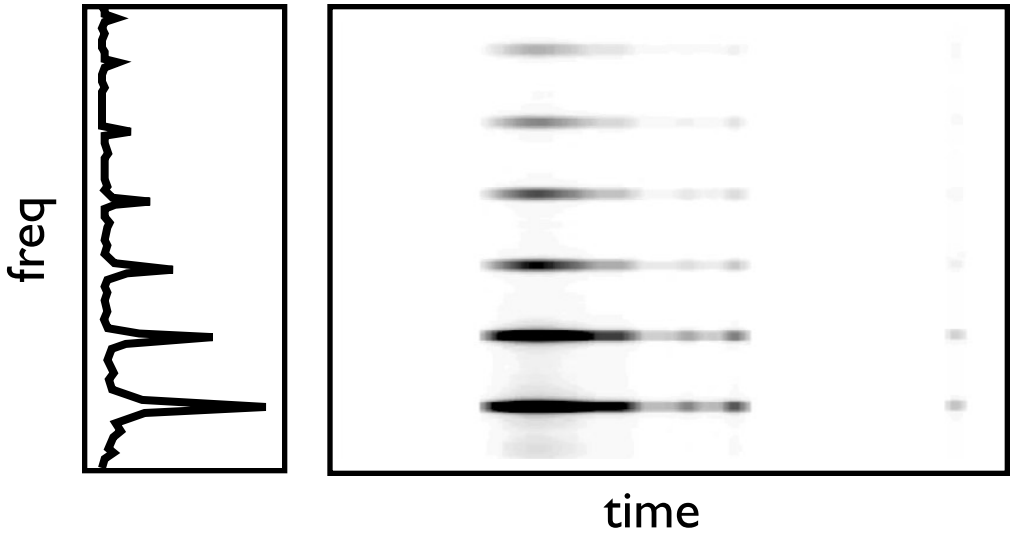




Berkeley
N L P

# Spectral Shape





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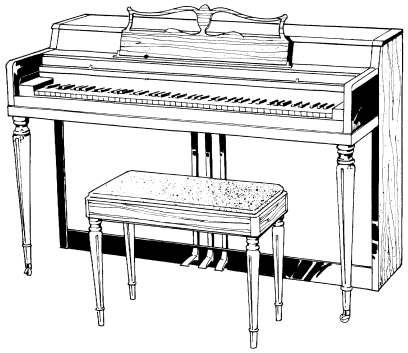
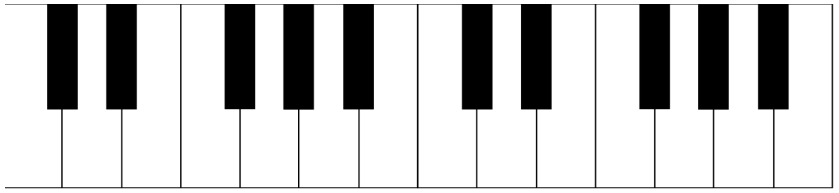
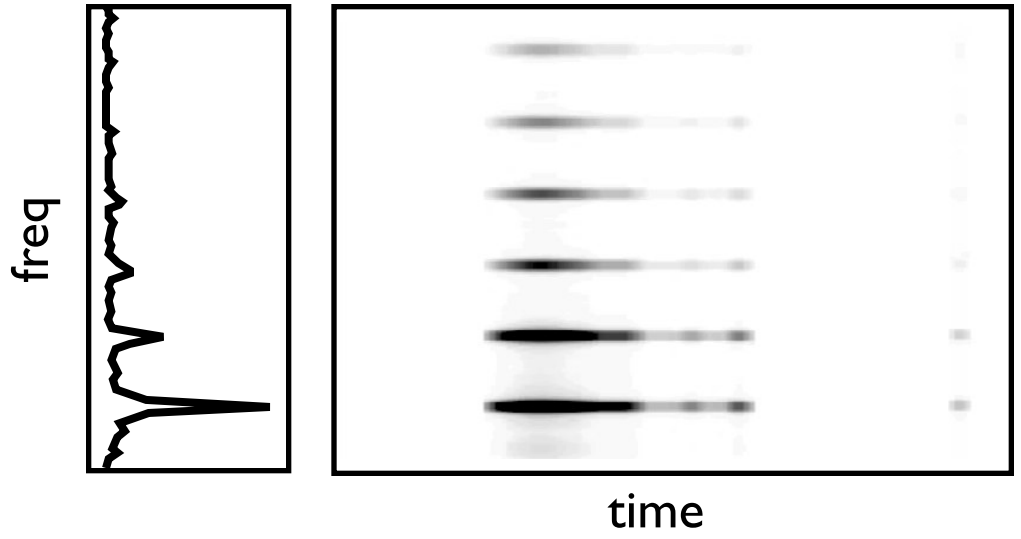
# Spectral Shape

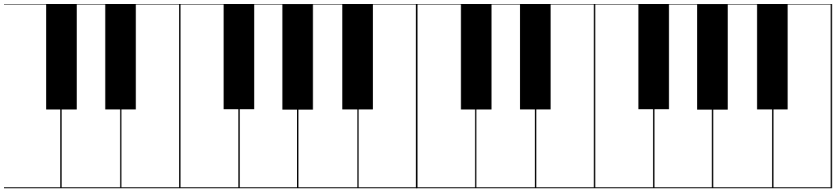


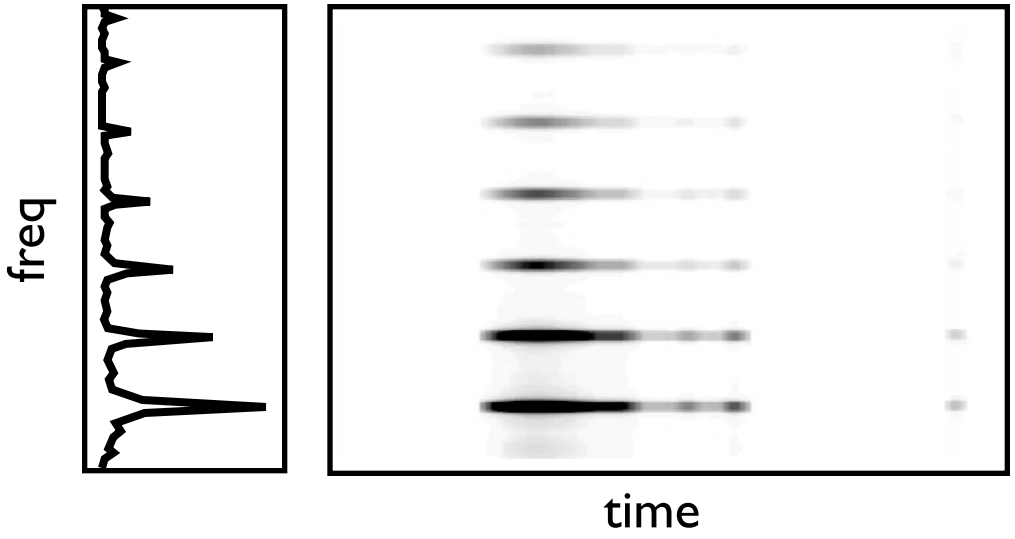




Berkeley
N L P

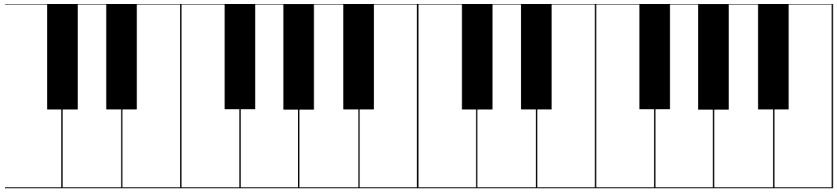
# Temporal Shape

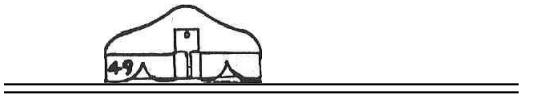


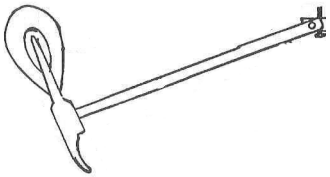


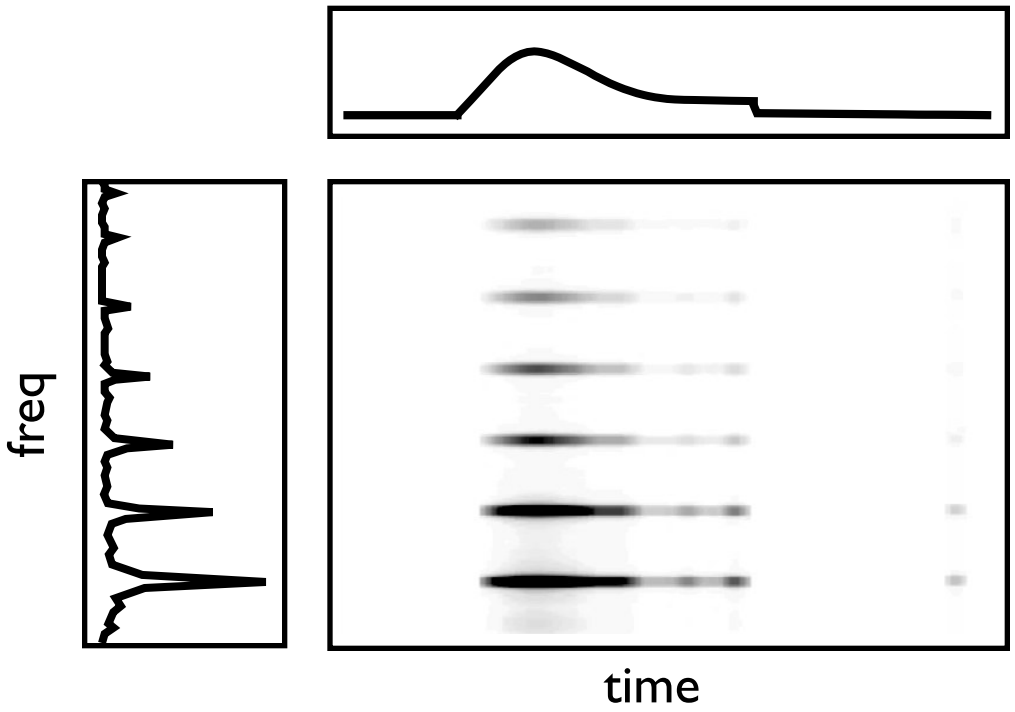
Berkeley
N L P

# Temporal Shape

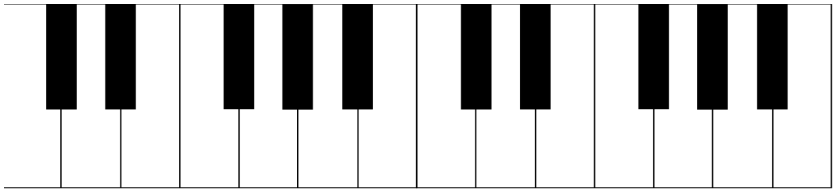


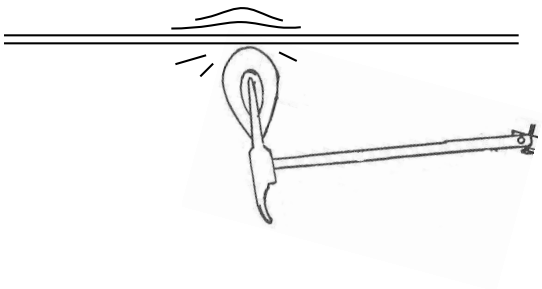


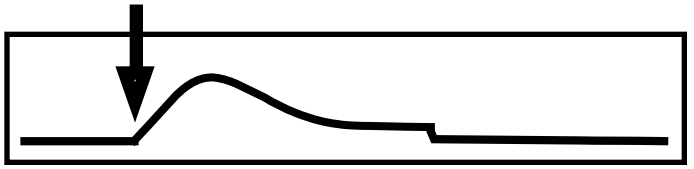


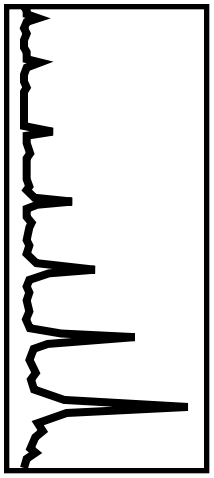


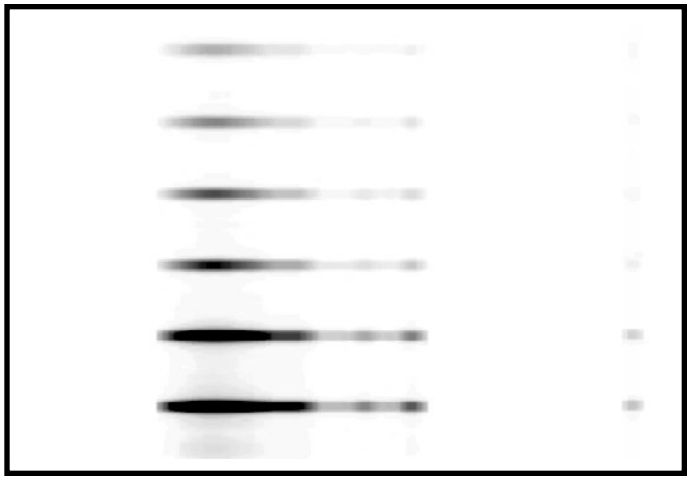
# Temporal Shape









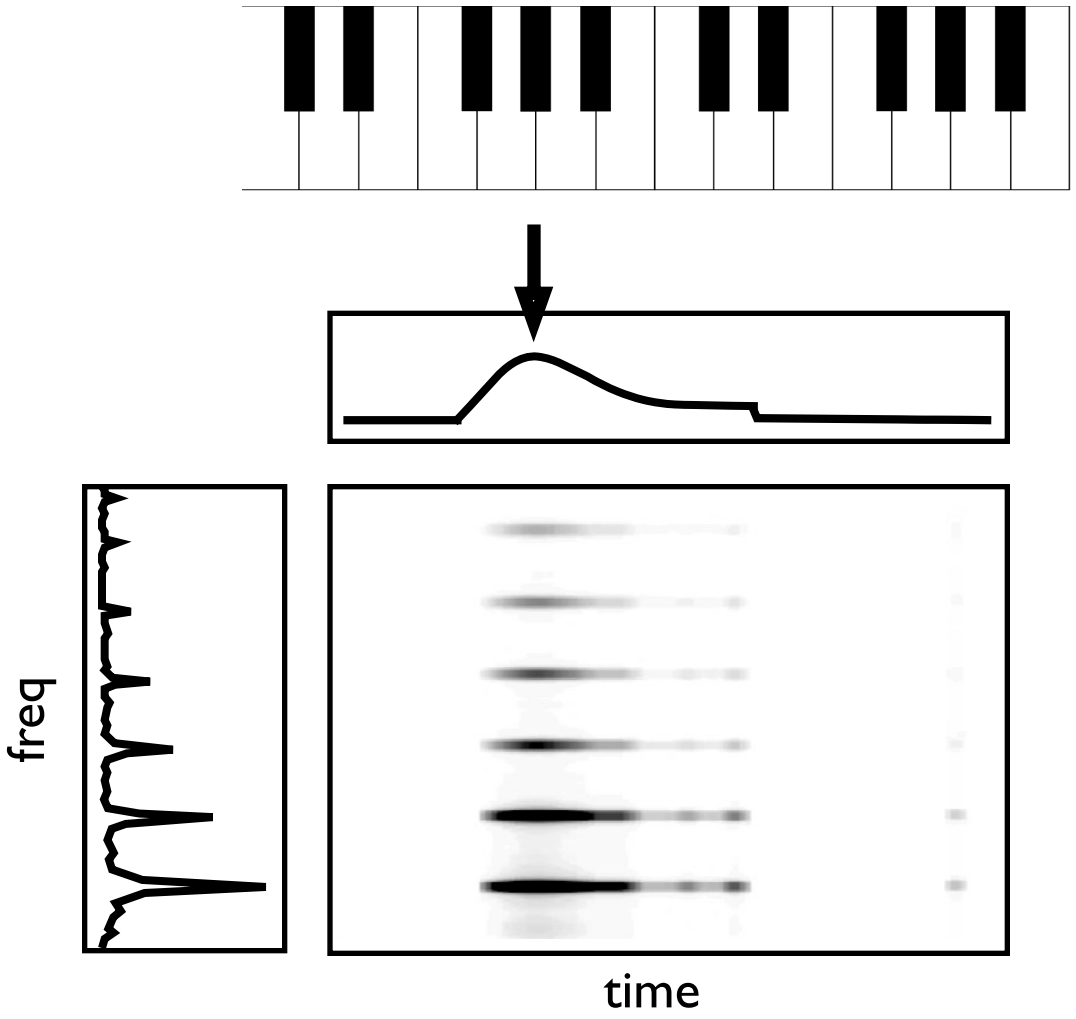


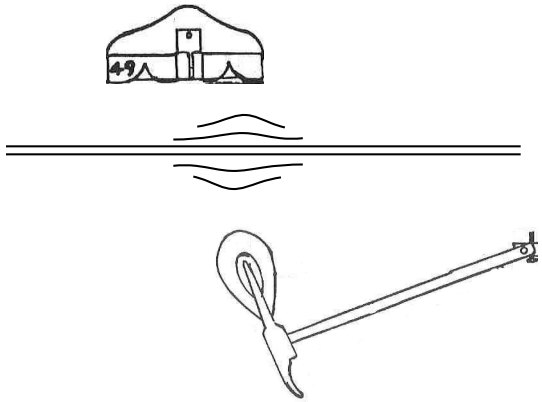
freq

time

Berkeley
N L P

# Temporal Shape



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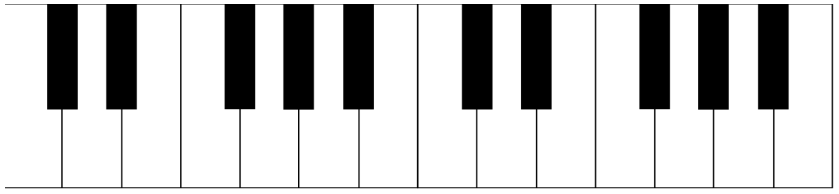
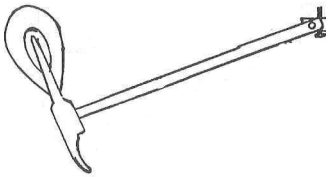
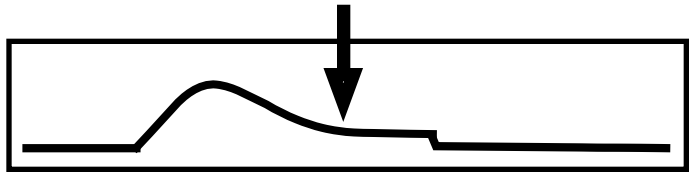
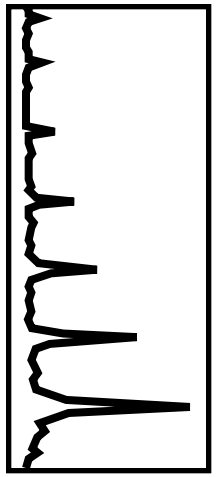
N L P

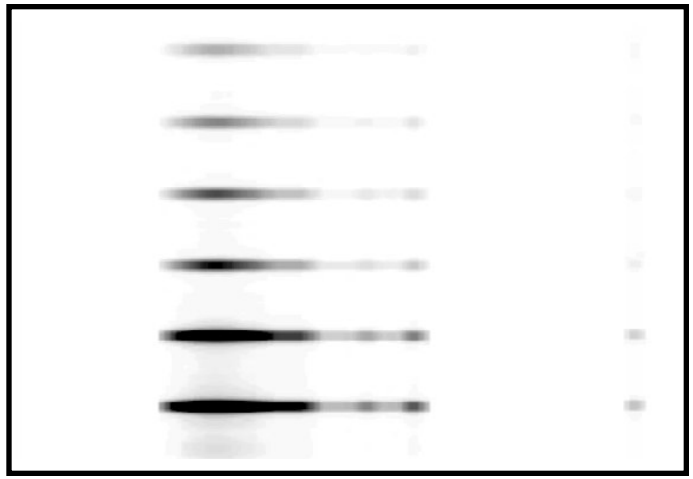
# Temporal Shape









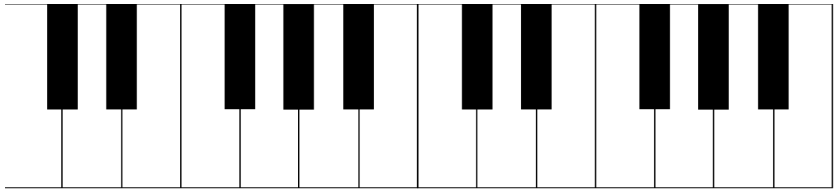


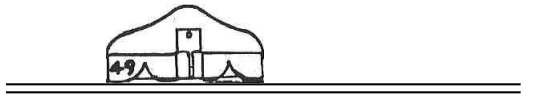
freq

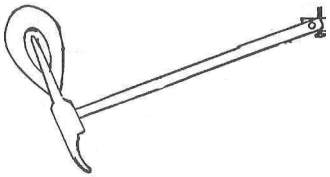
time

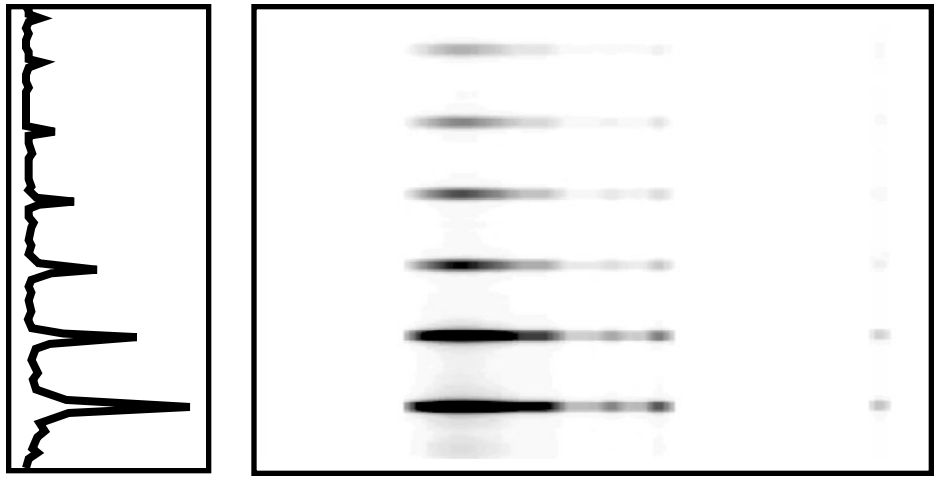
Berkeley
N L P

# Temporal Shape



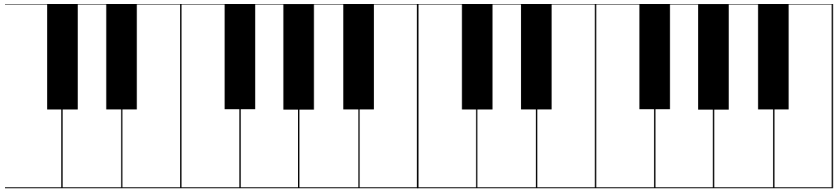


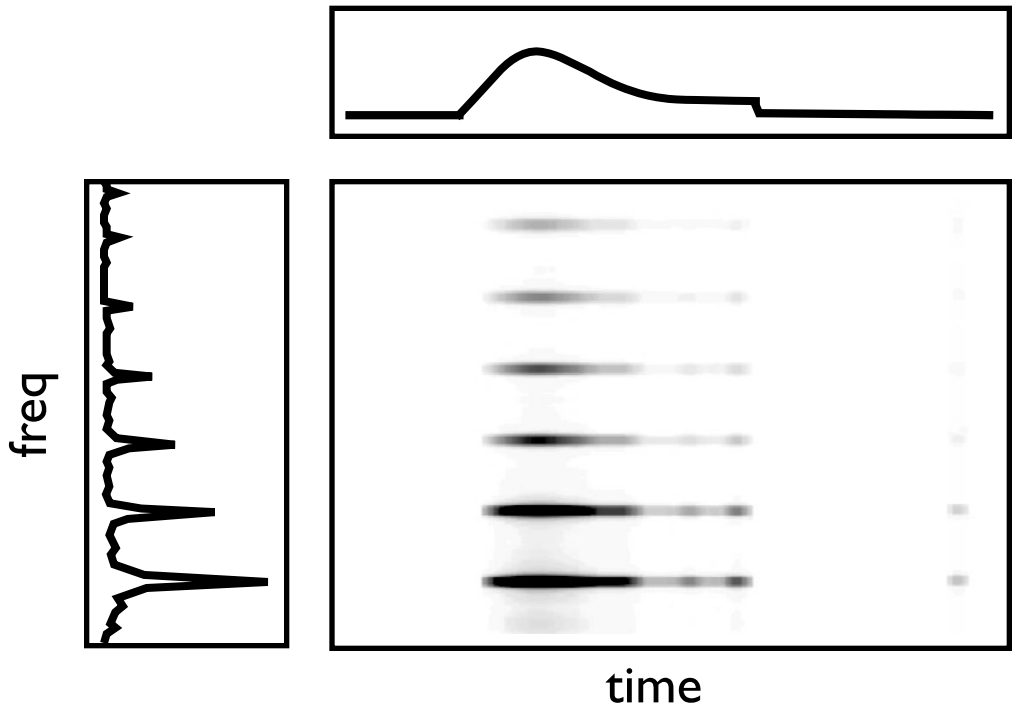




Berkeley
N L P

# Temporal Shape





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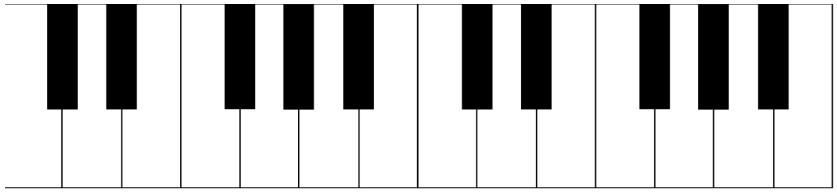
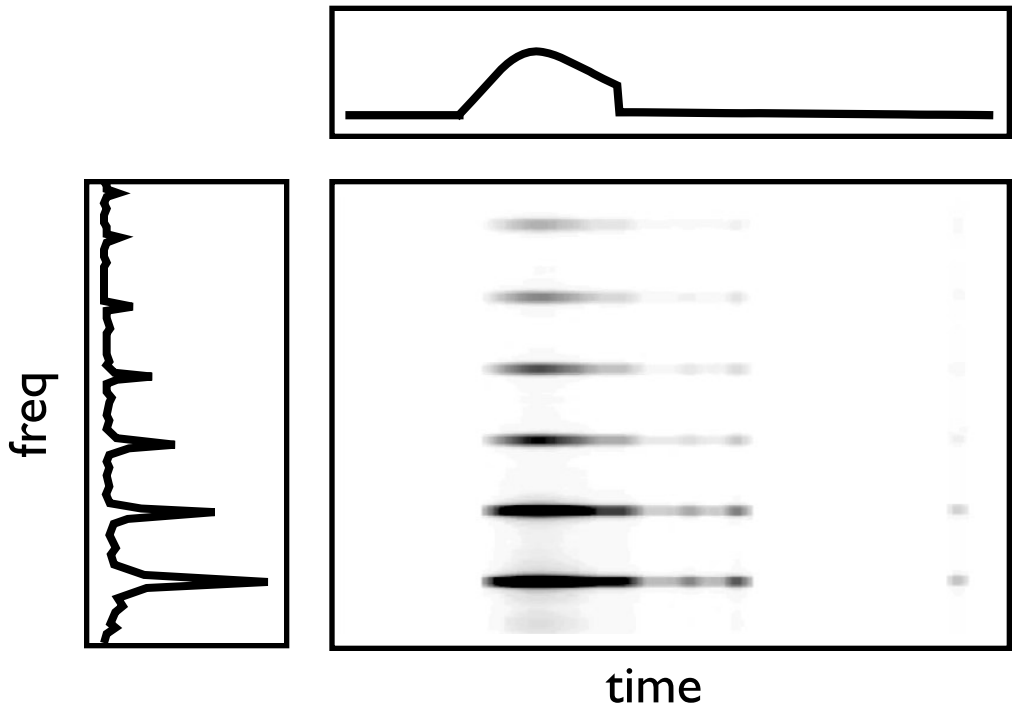
N L P

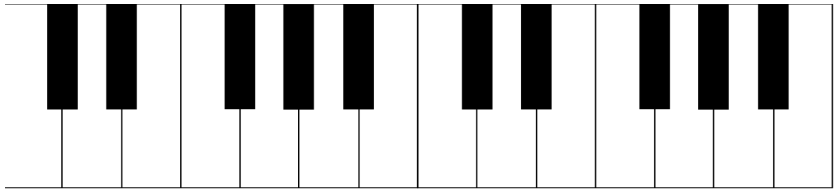
# Temporal Shape

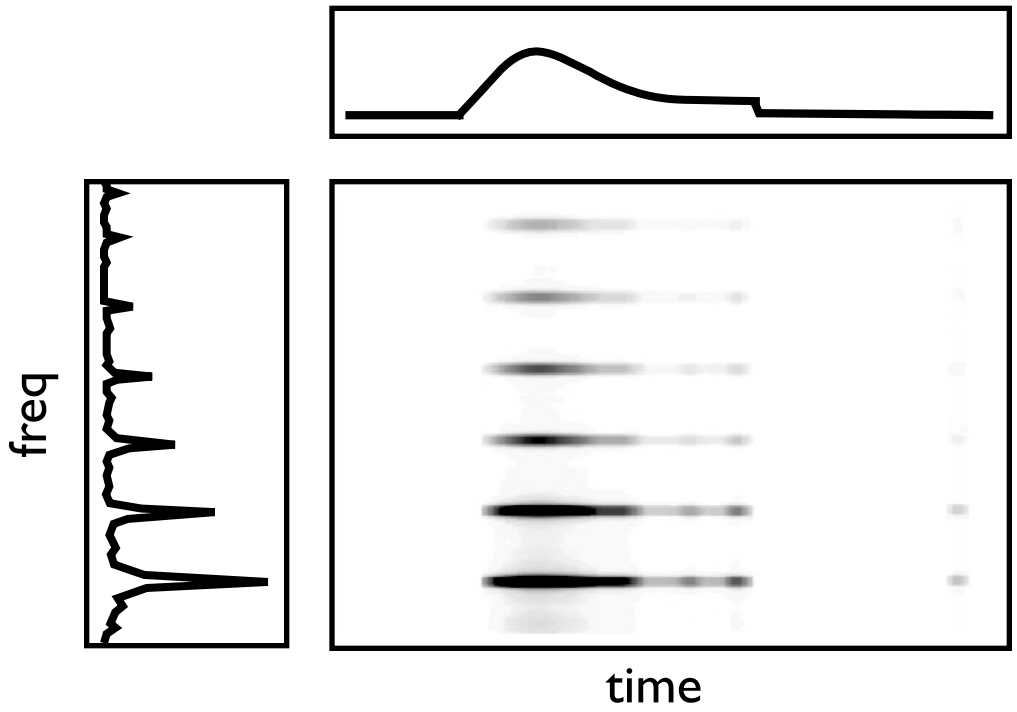




Berkeley
N L P

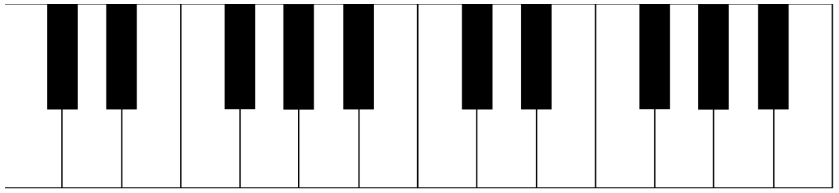
# Temporal Shape

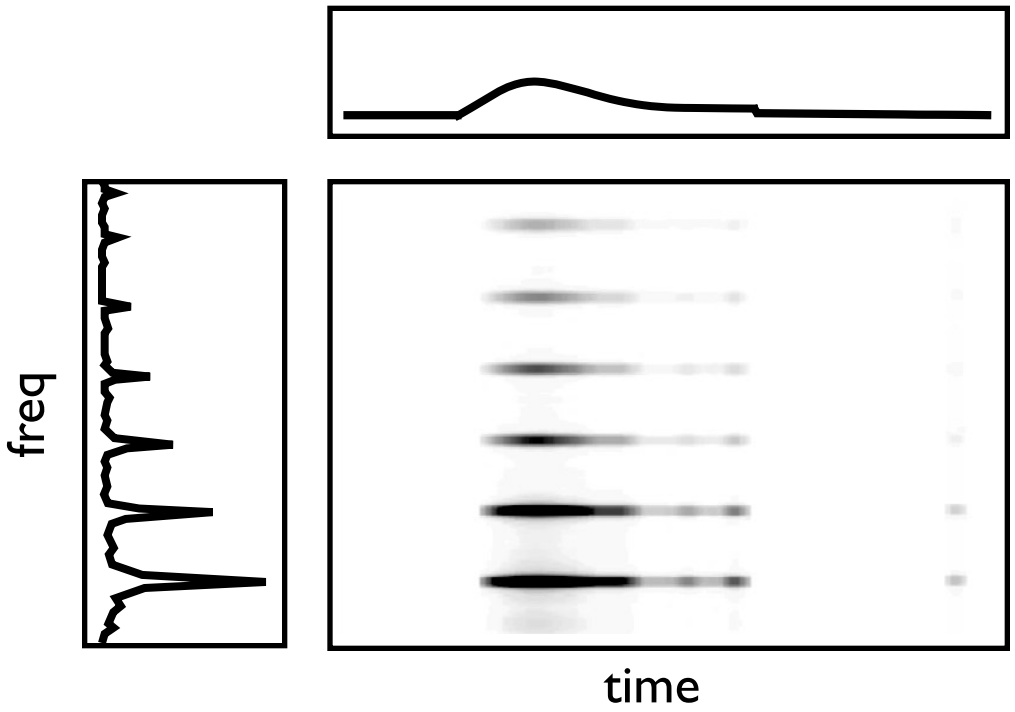




Berkeley
N L P

# Temporal Shape





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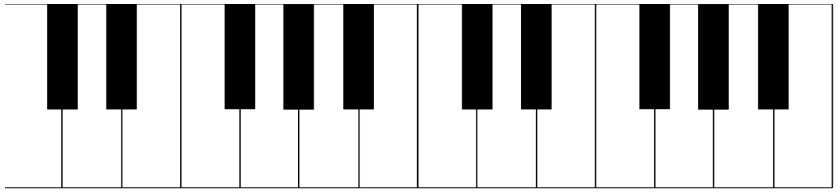
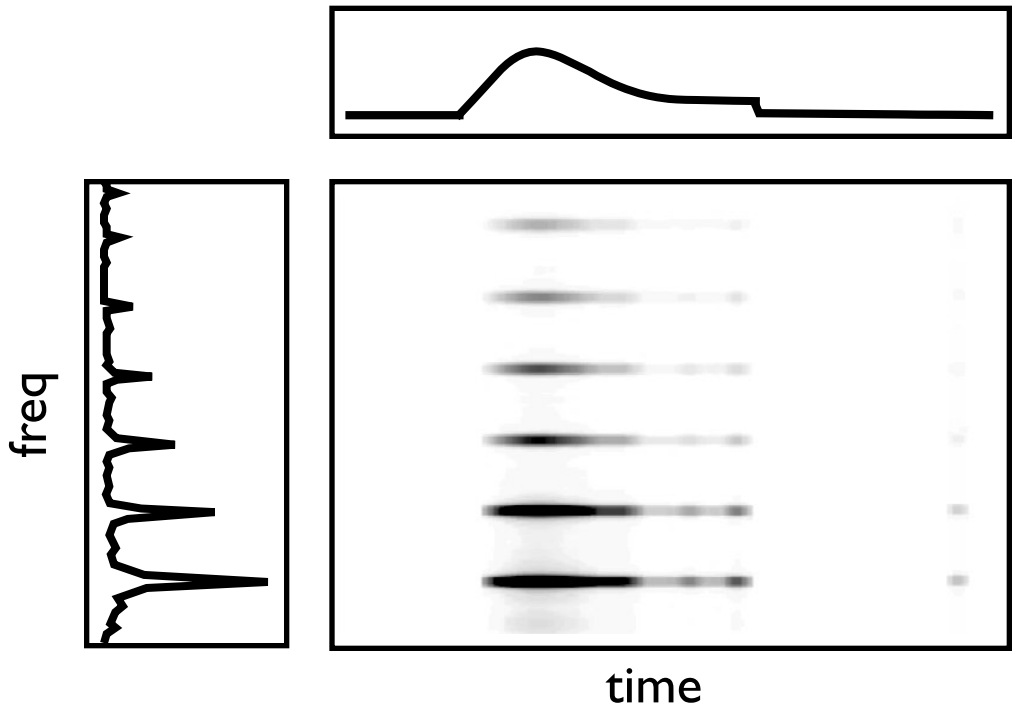
# Temporal Shape





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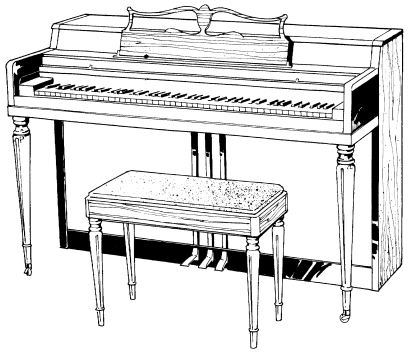
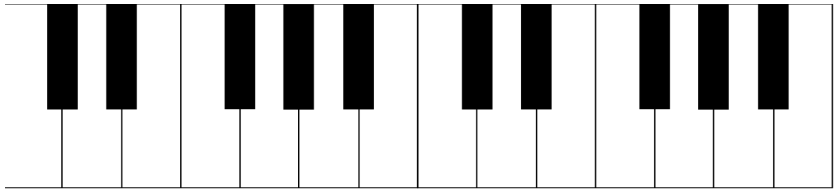
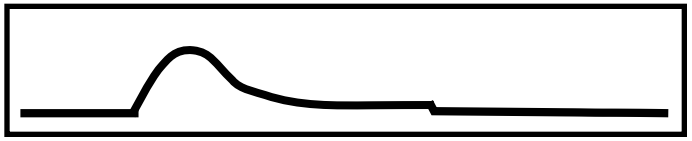
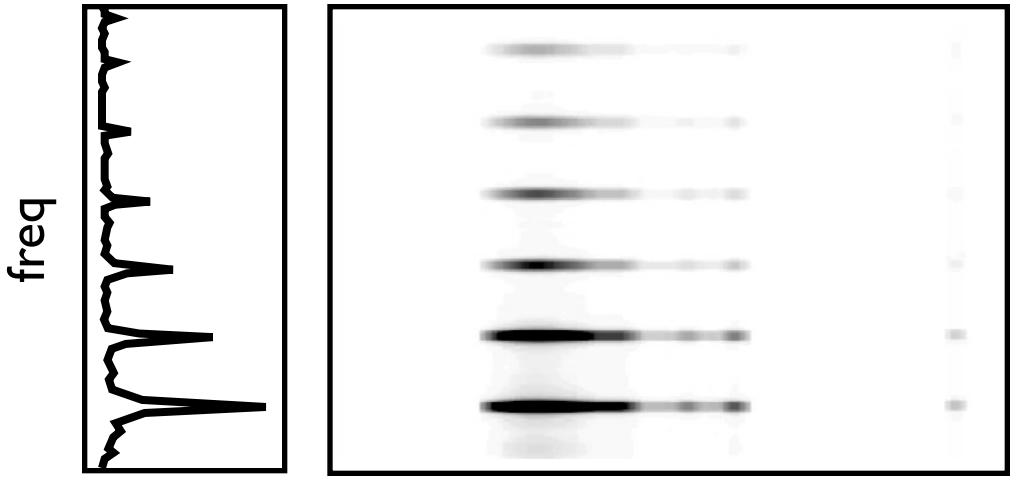
# Temporal Shape









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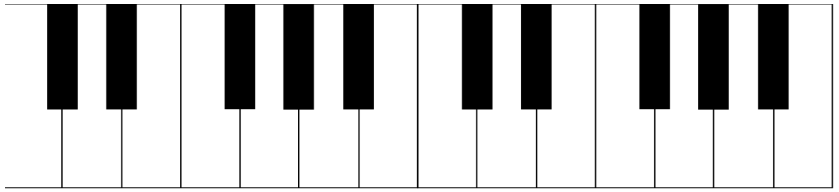
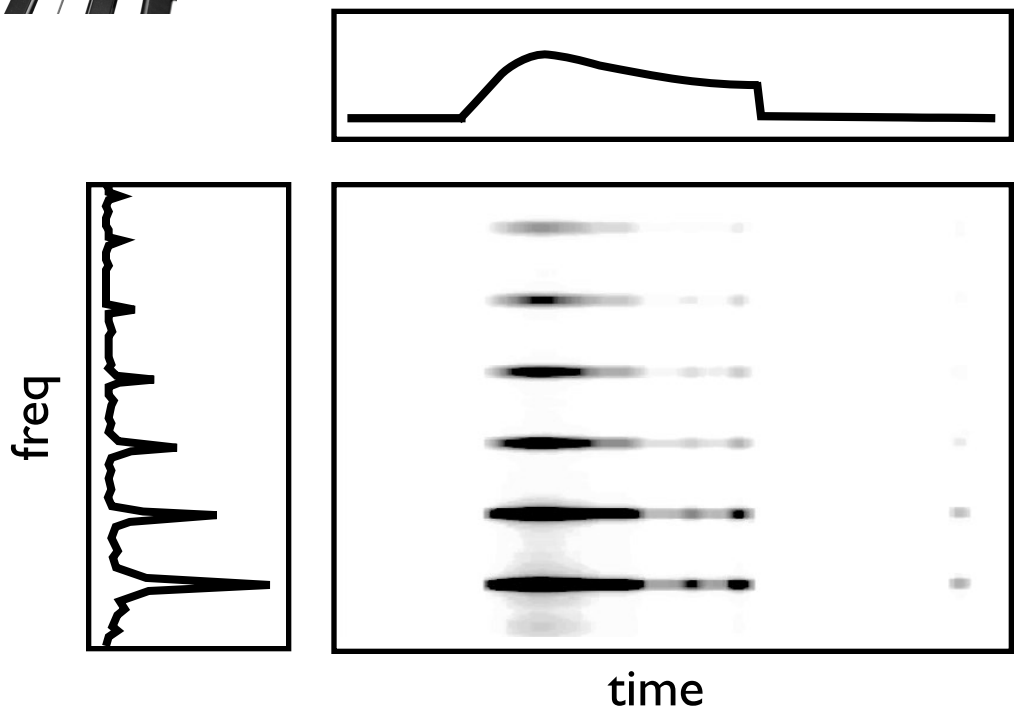
# Temporal Shape



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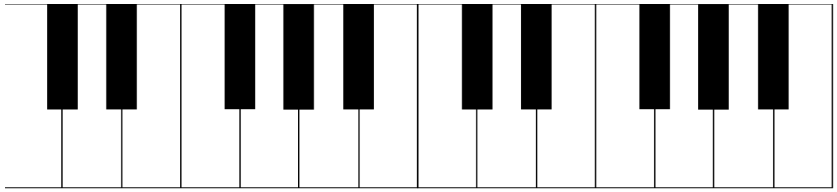

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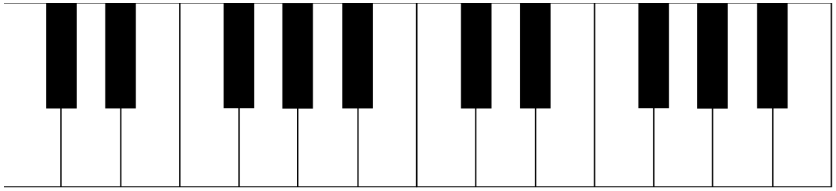
# Polyphony



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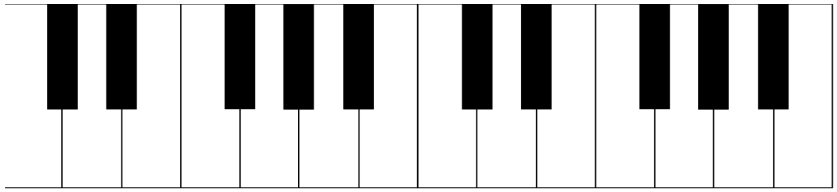

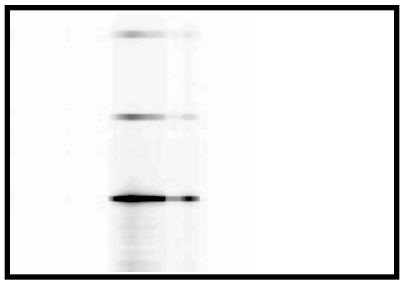

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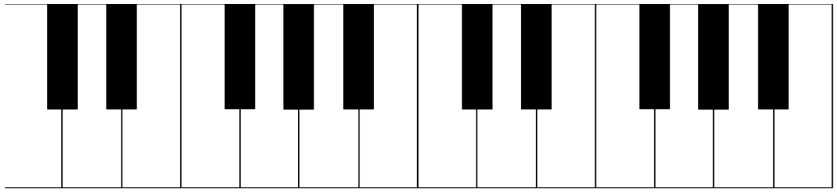
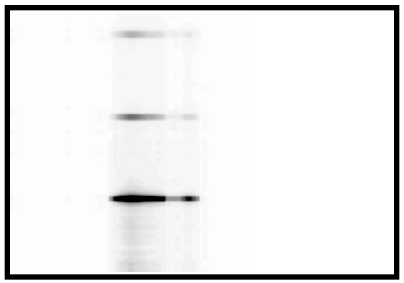
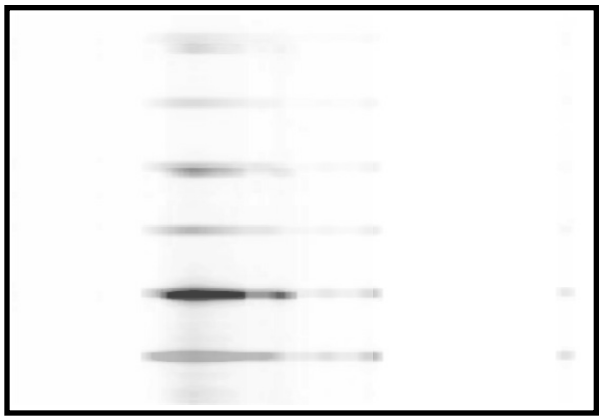
# Polyphony







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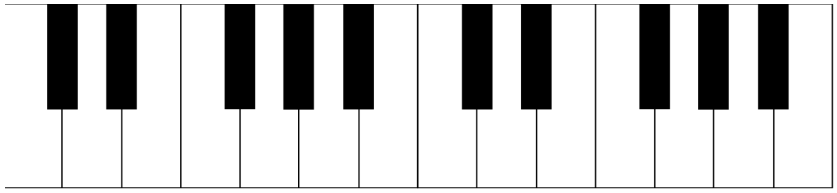

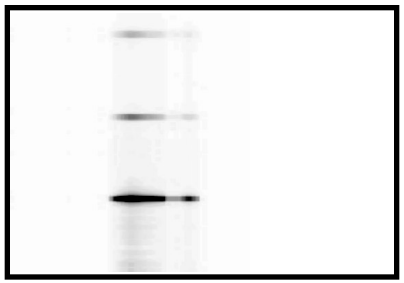

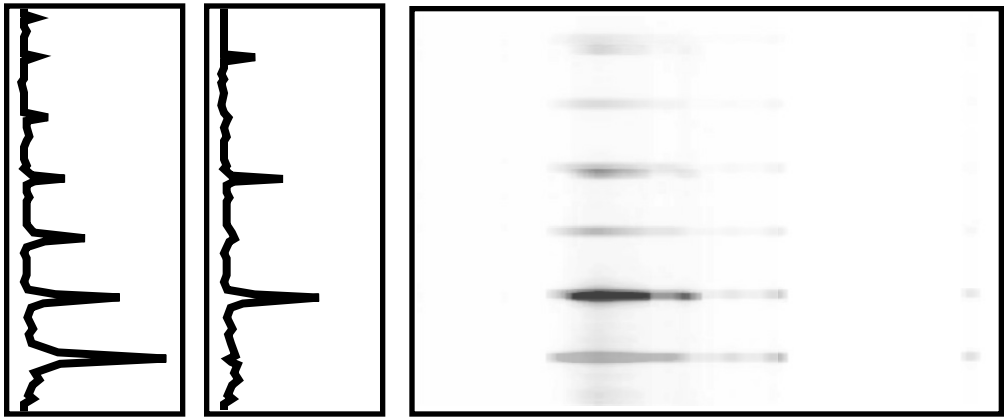

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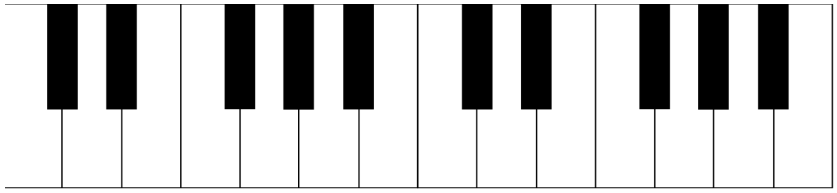
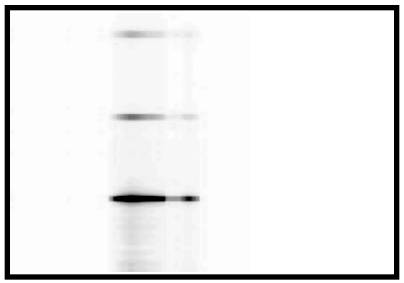
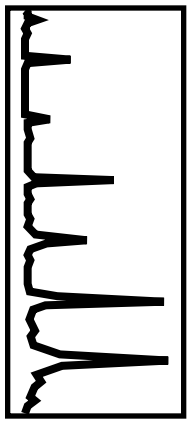
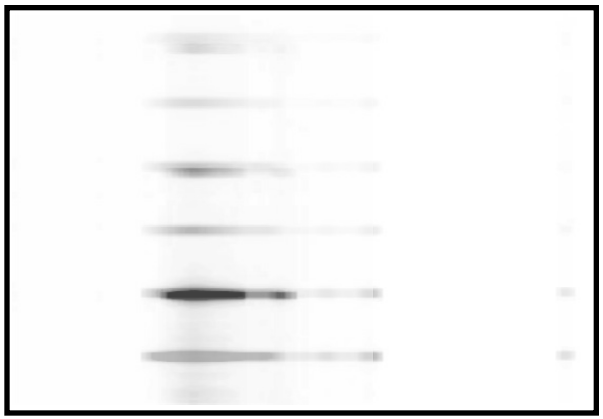
# Polyphony









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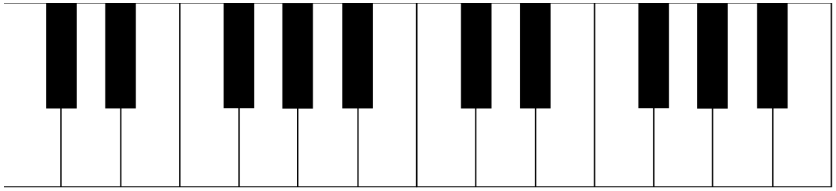
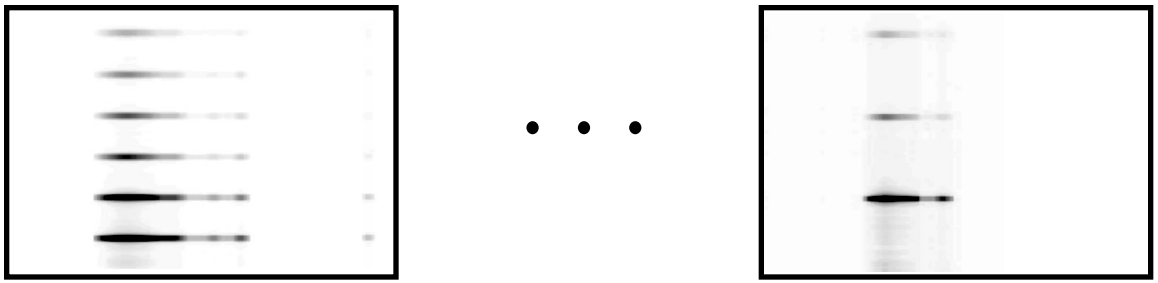
# Polyphony





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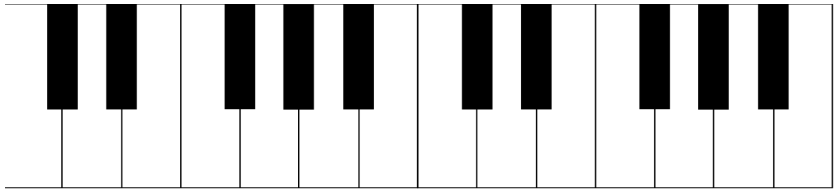
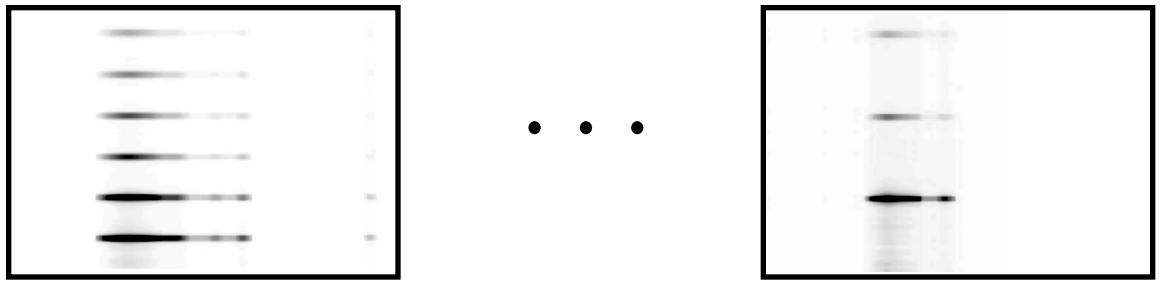
# Polyphony





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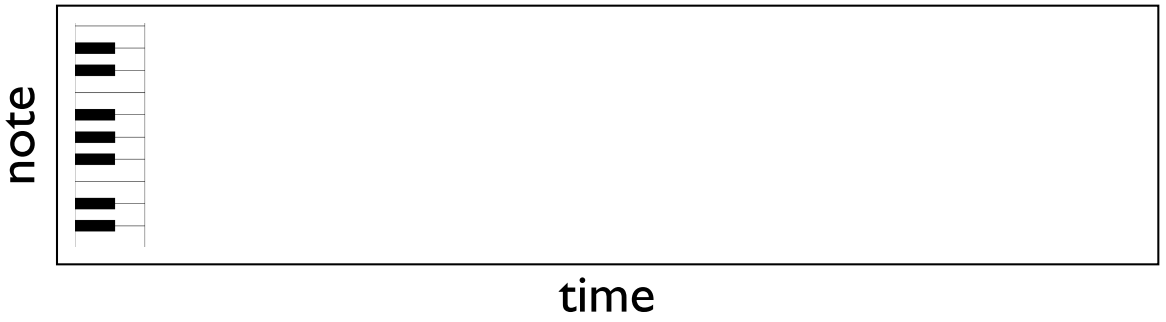
# Generative Model



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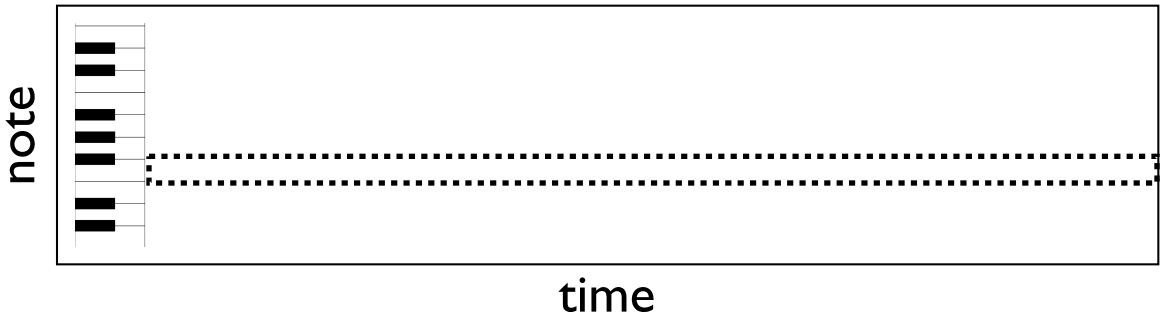
# Generative Model



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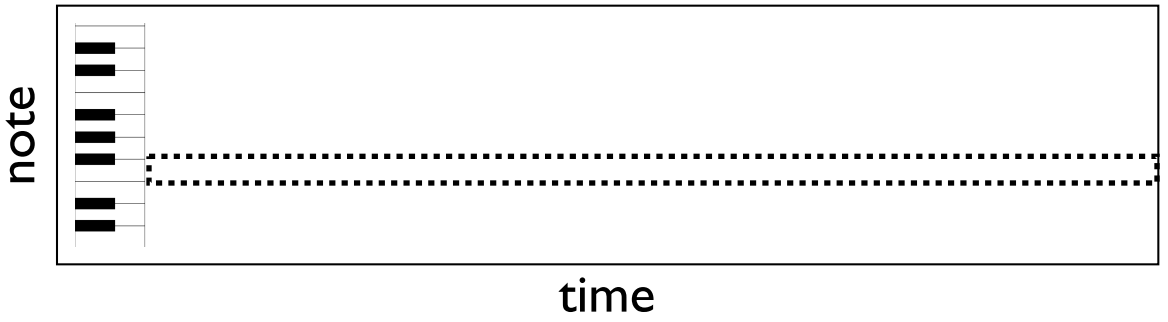
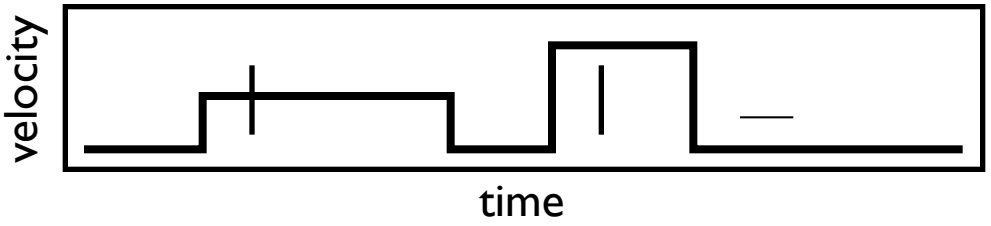
# Generative Model




Note events



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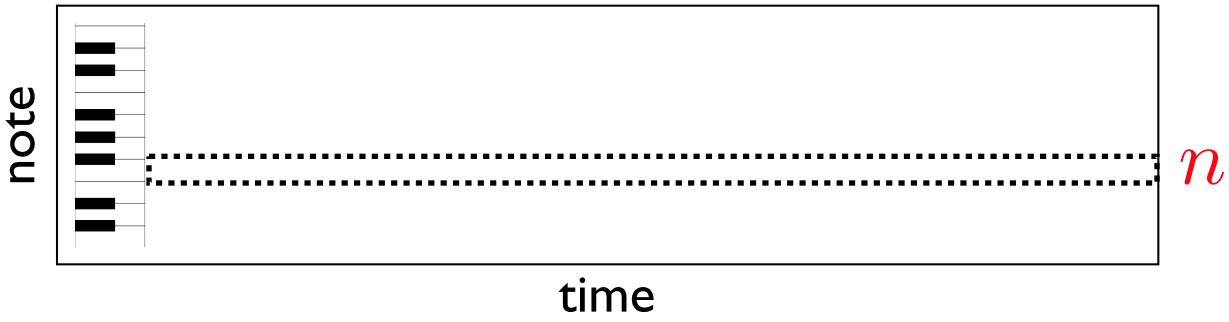
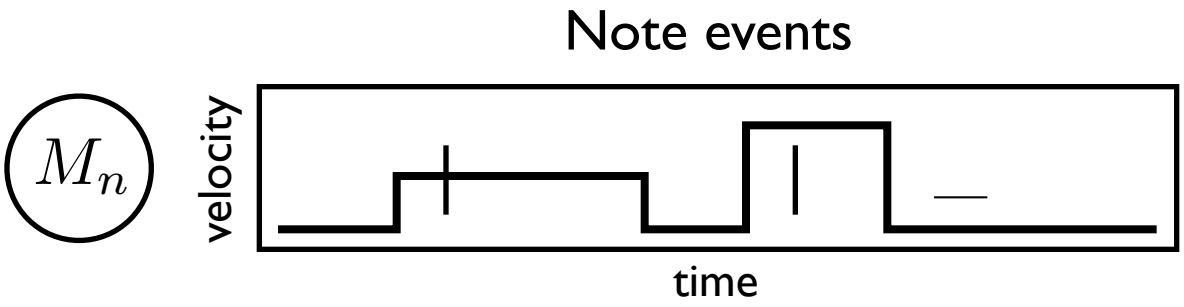
# Generative Model



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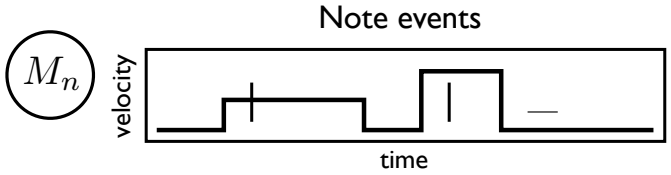
# Generative Model



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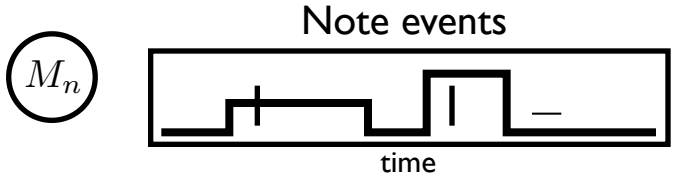
N L P

# Generative Model



Berkeley
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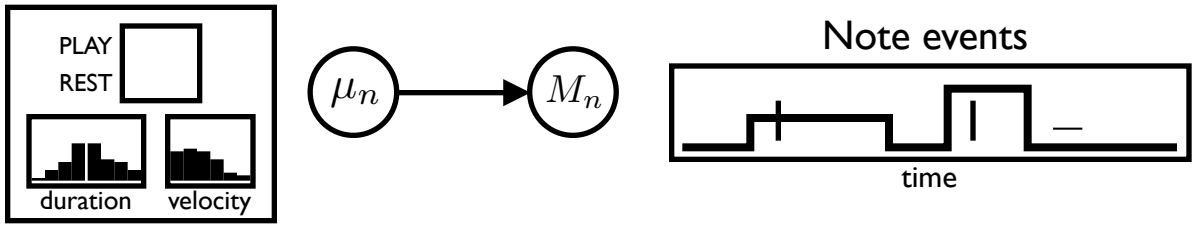

Berkeley
N L P

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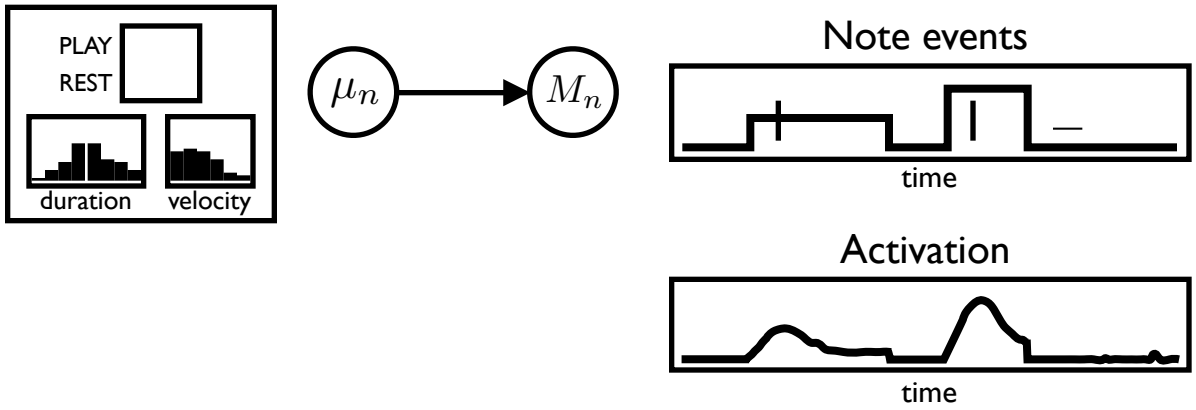

Berkeley
N L P

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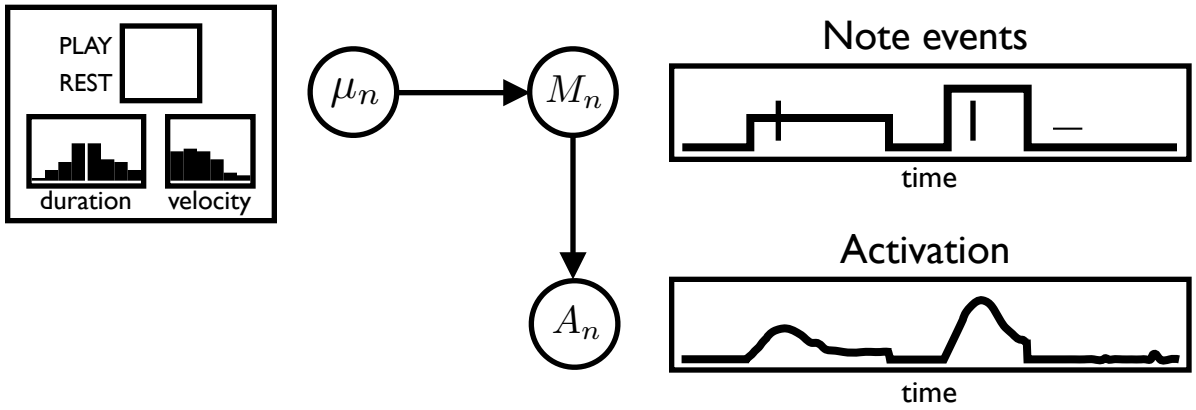

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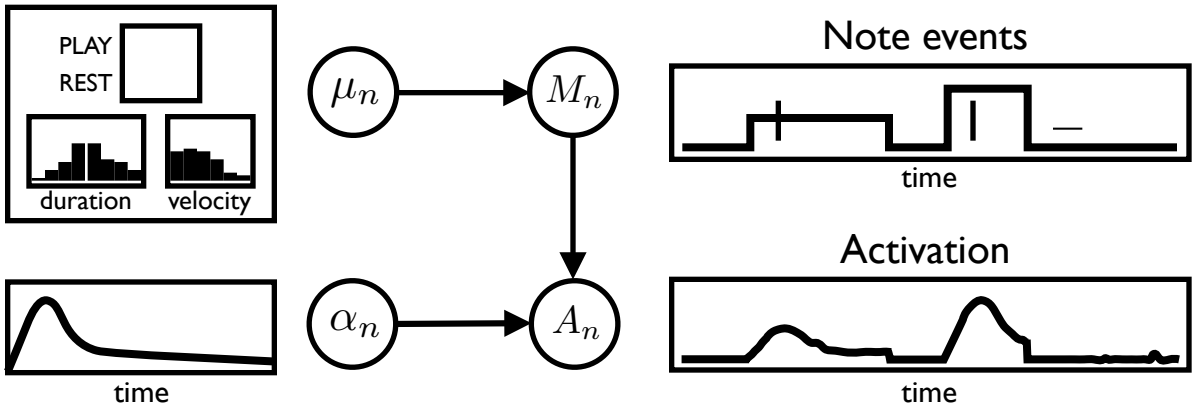
# Generative Model



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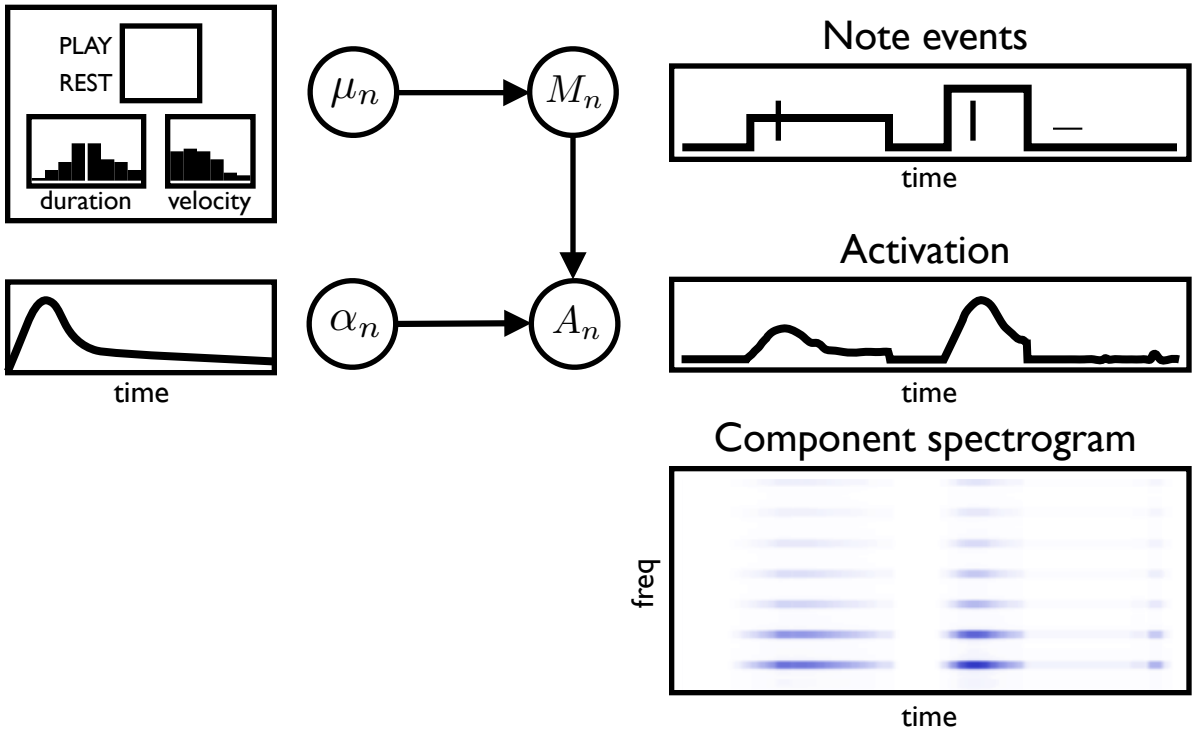

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N L P

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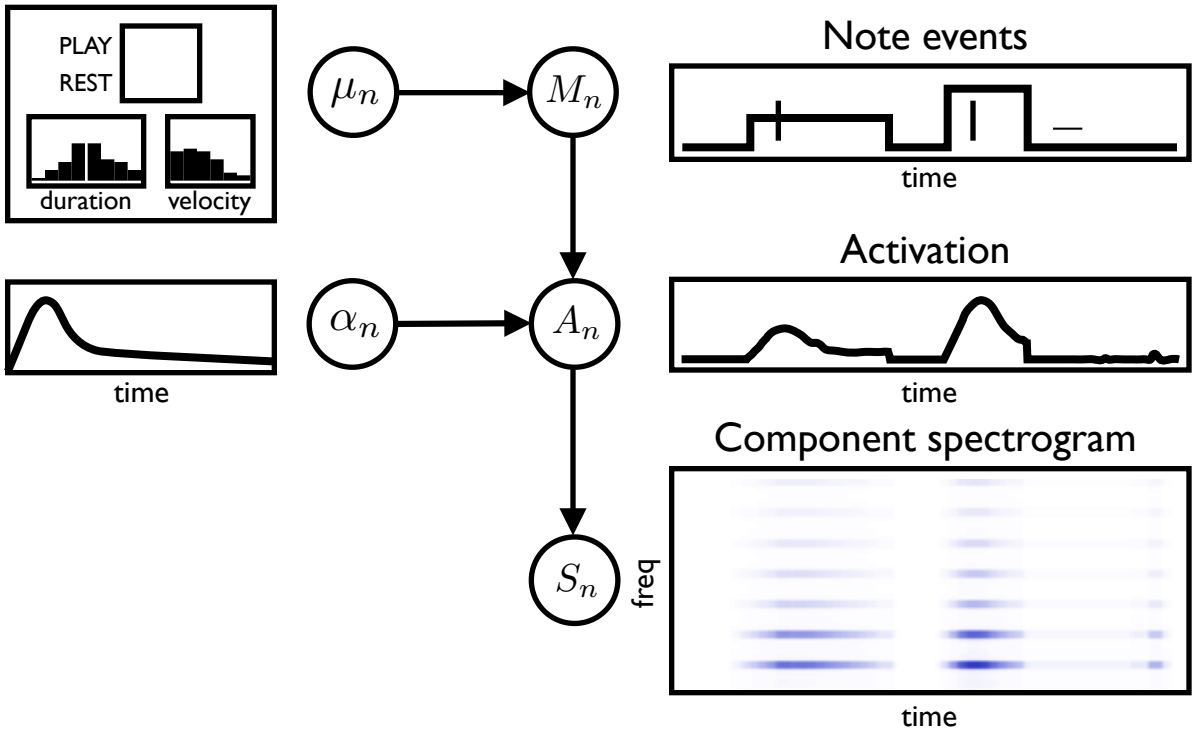

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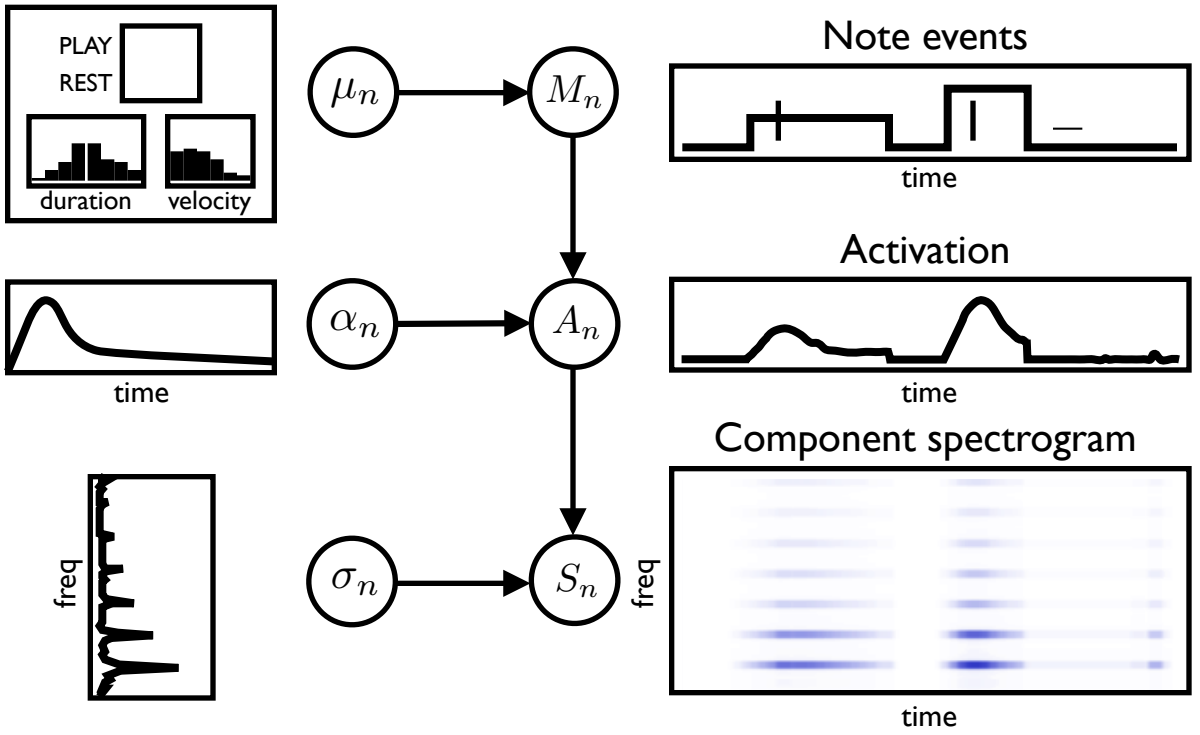

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N L P

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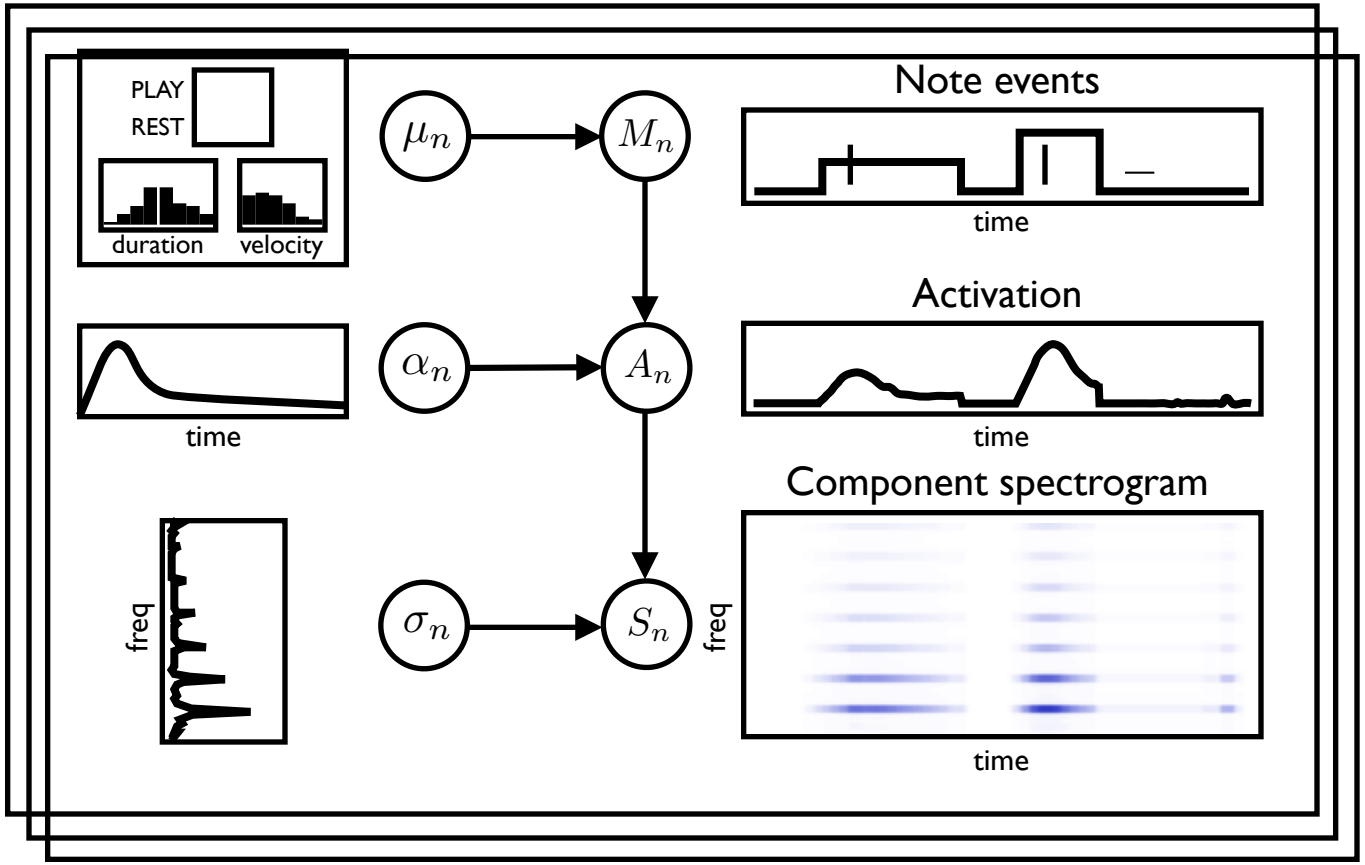

Berkeley
N L P

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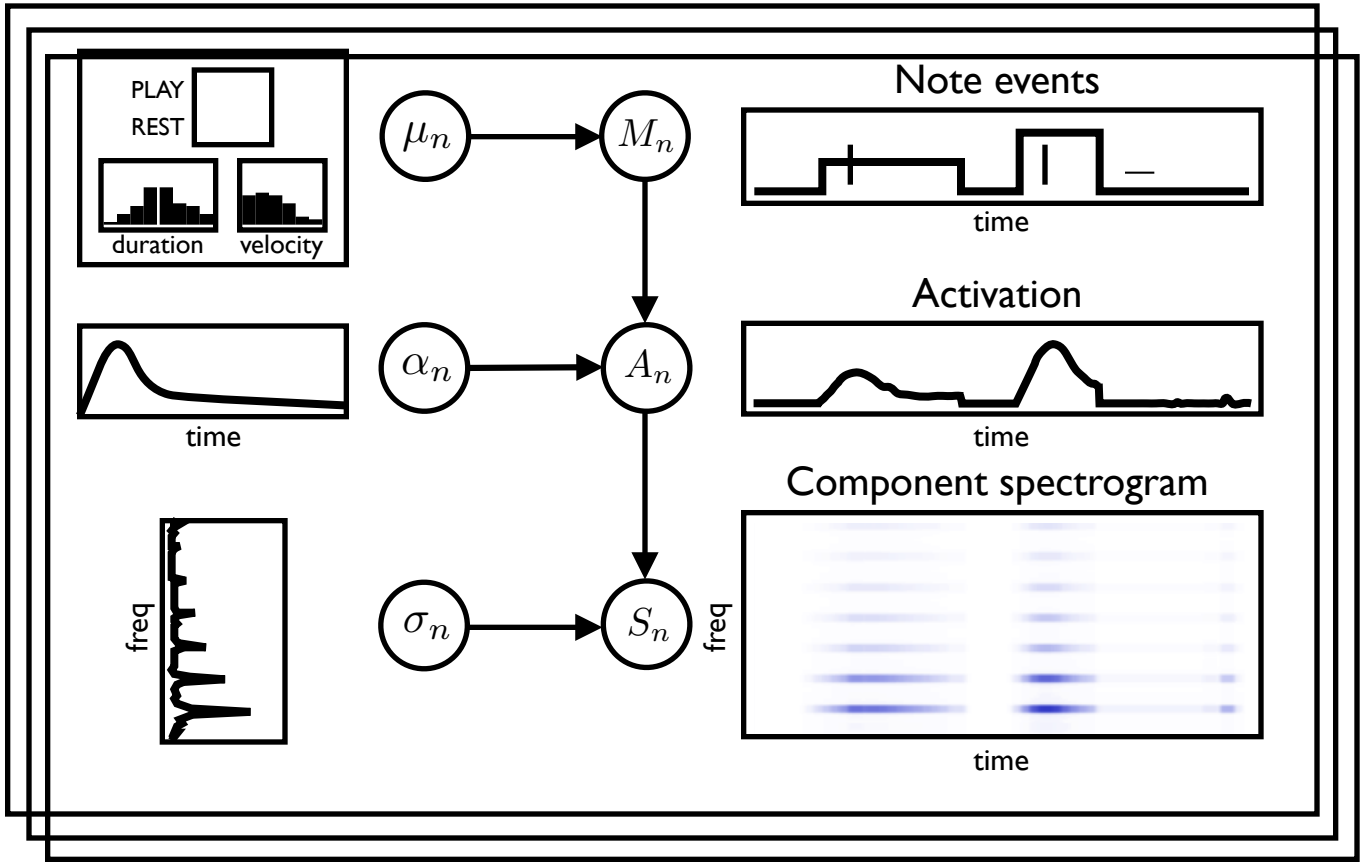


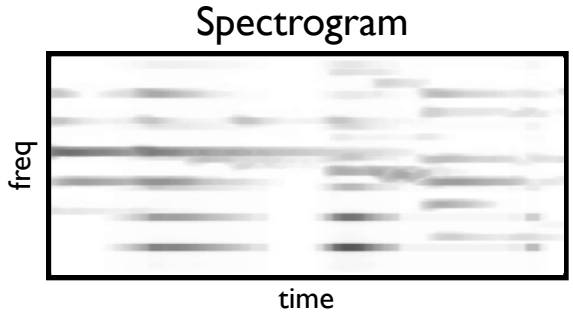

Berkeley
N L P

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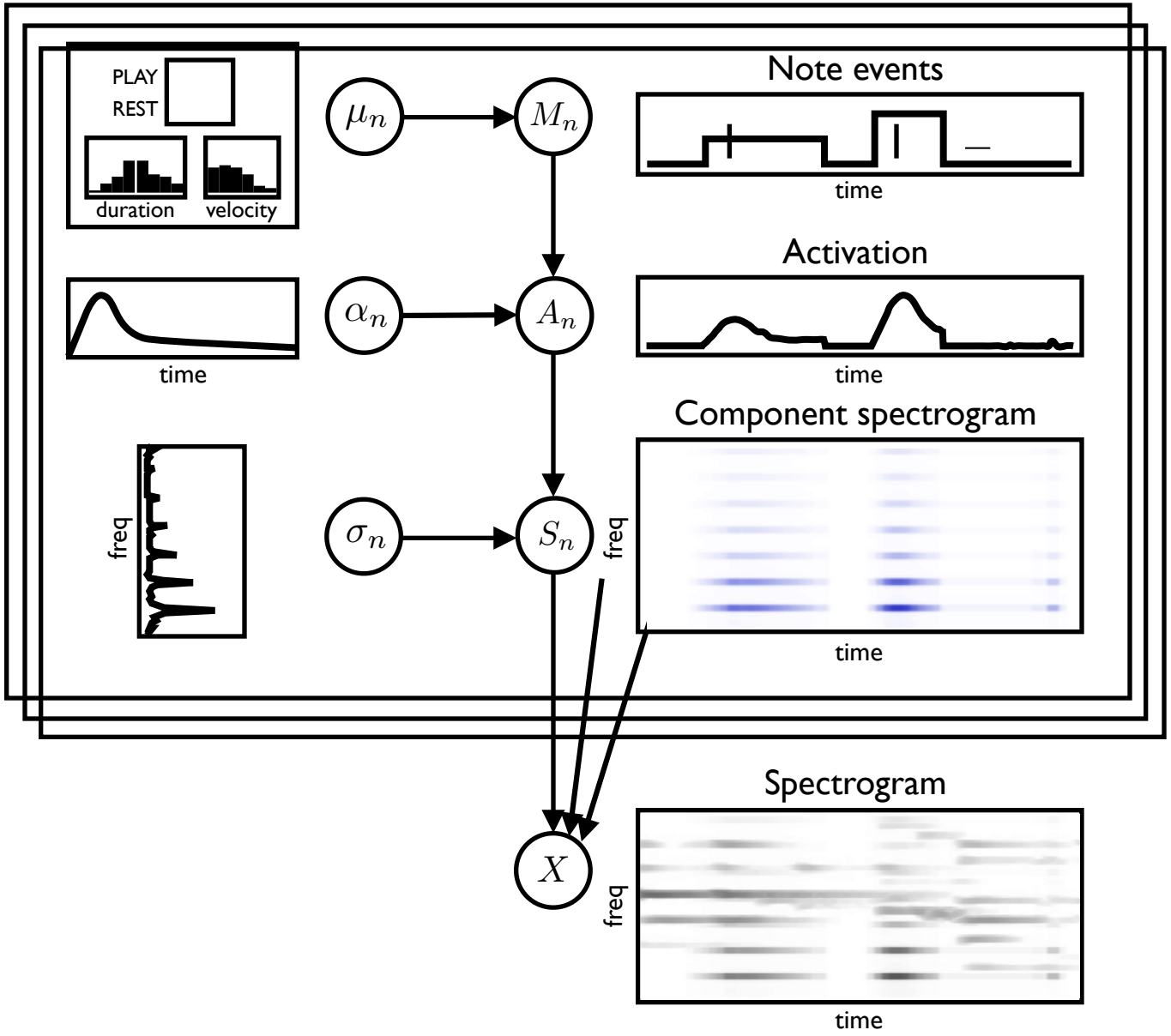

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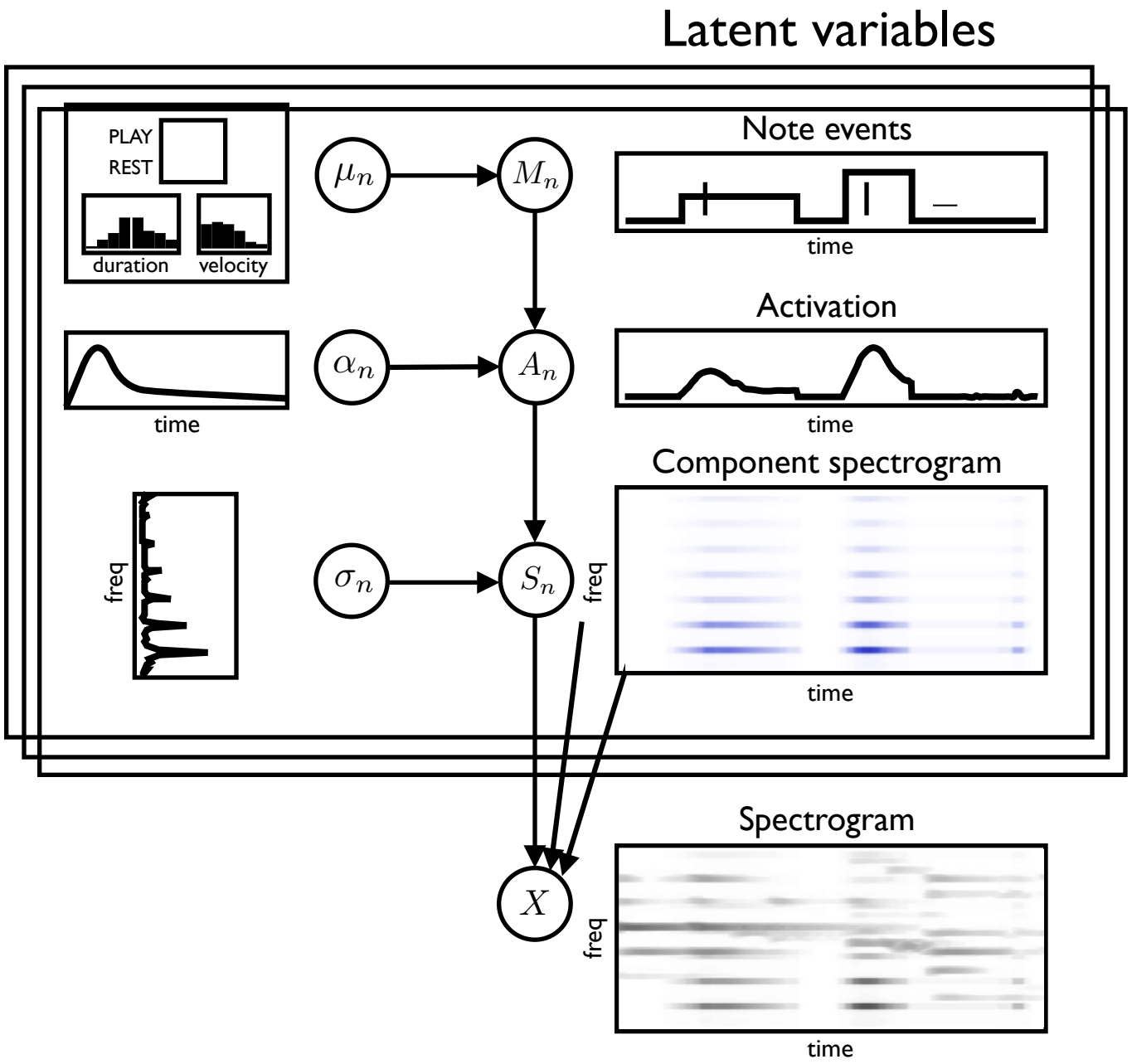
# Generative Model



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N L P

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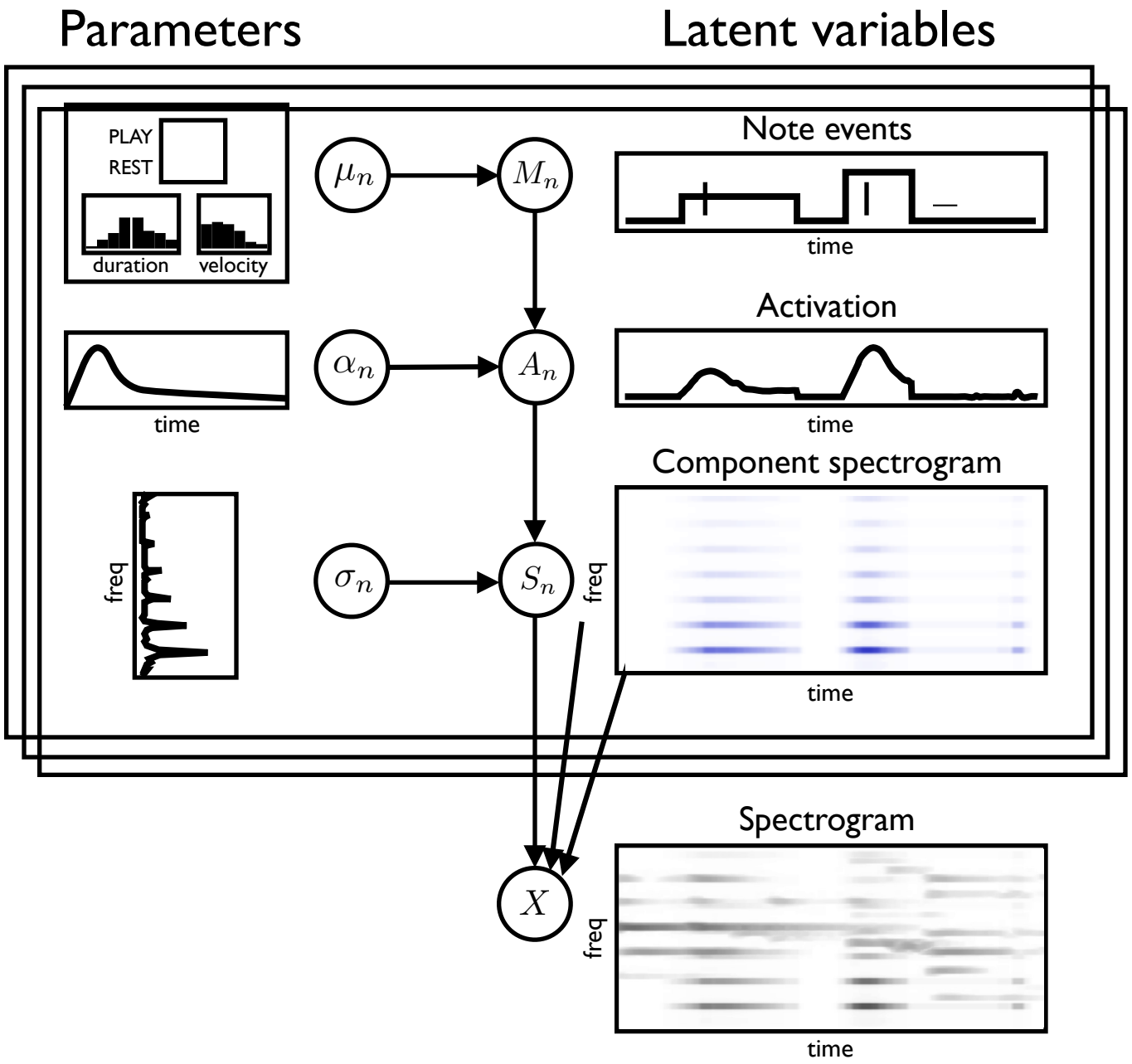


# Note Event Model

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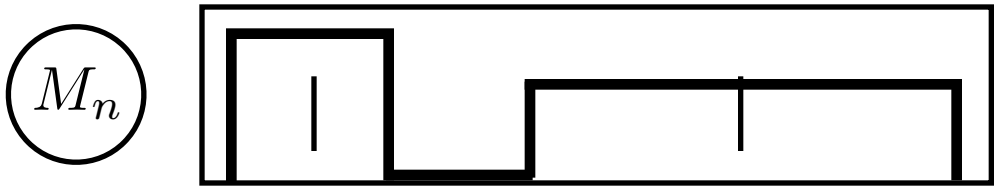
# Note Event Model



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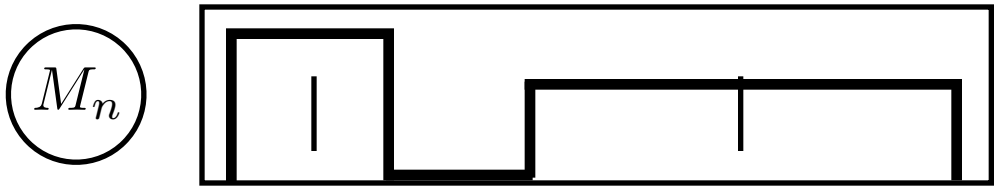
# Note Event Model



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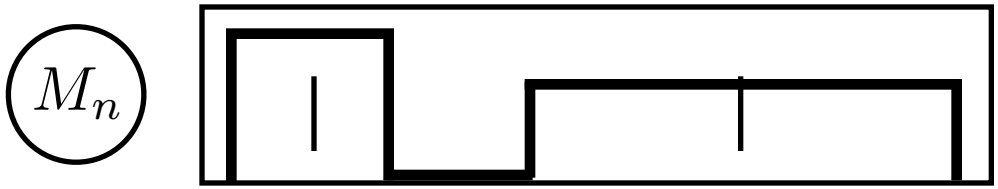
N L P

# Note Event Model




Event type

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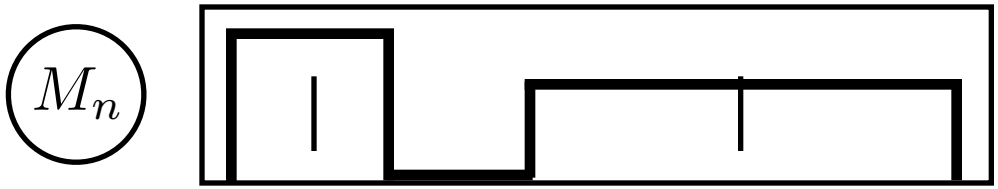
# Note Event Model




Event type

PLAY

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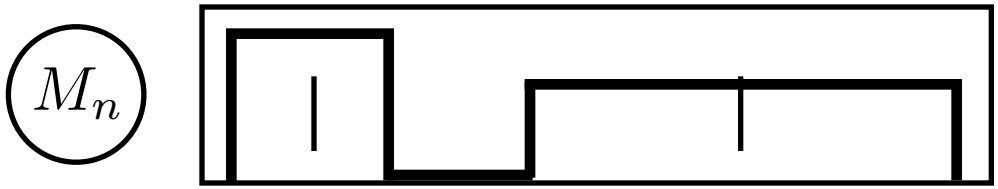
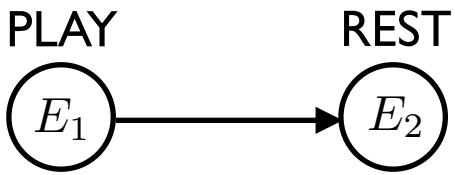
# Note Event Model




Event type



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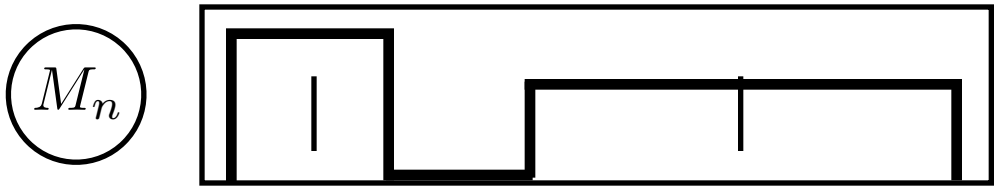
# Note Event Model

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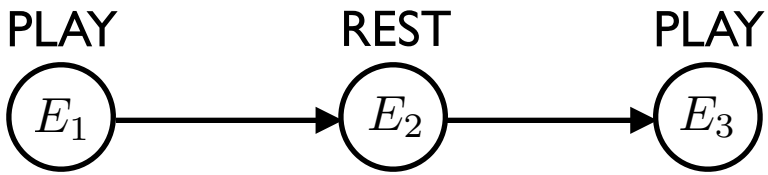

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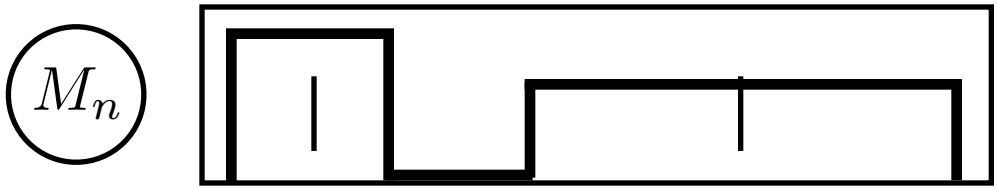
# Note Event Model

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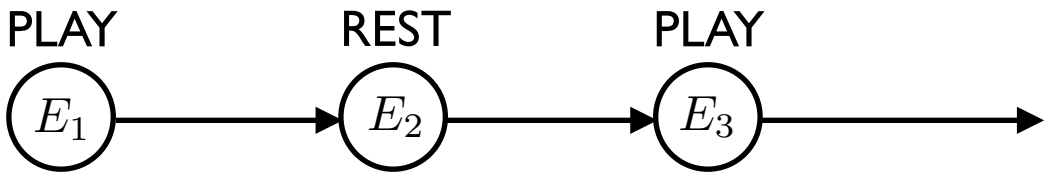

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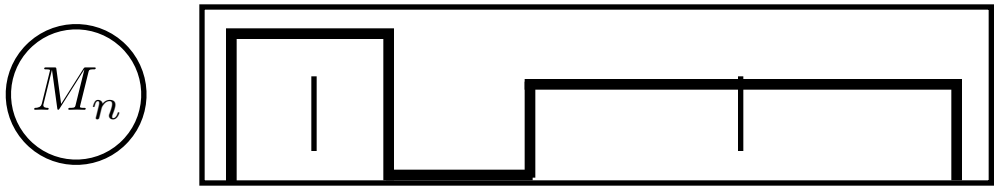
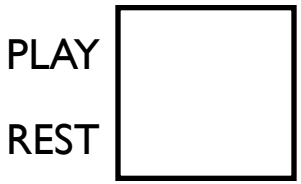
# Note Event Model

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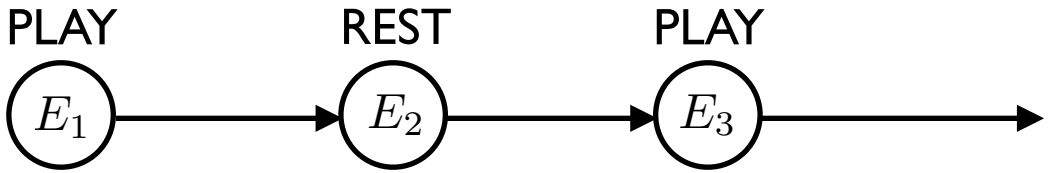

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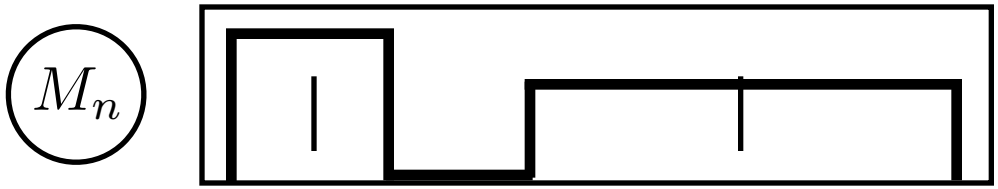


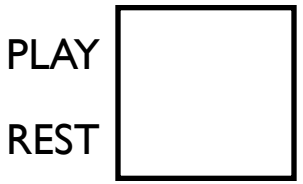


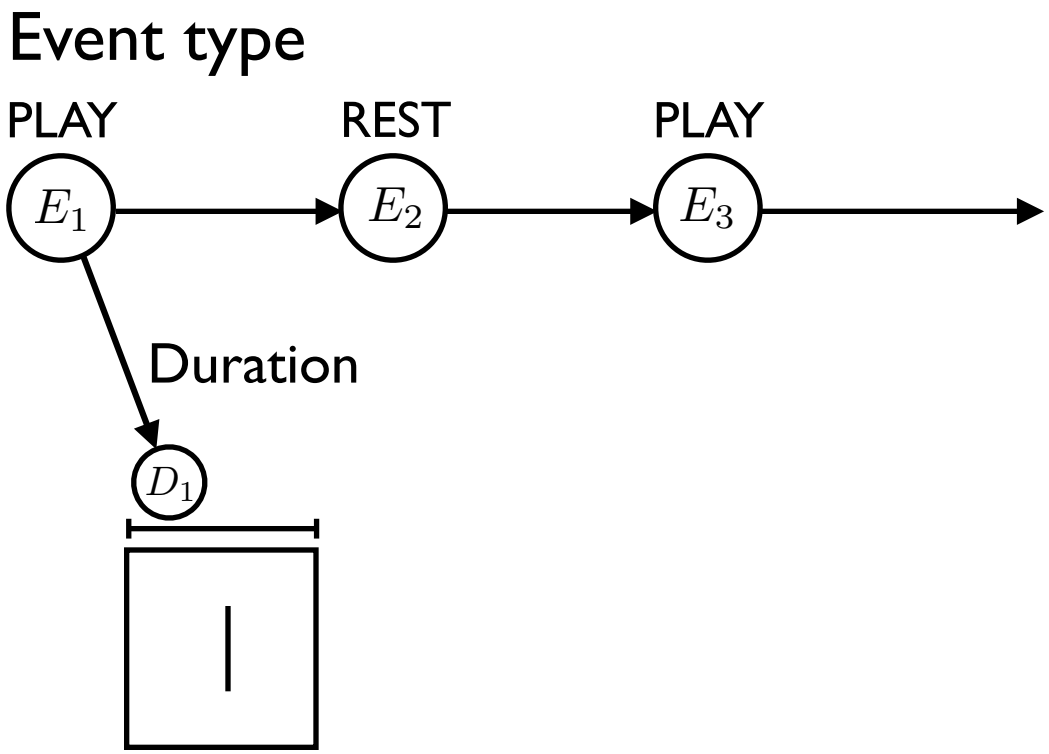

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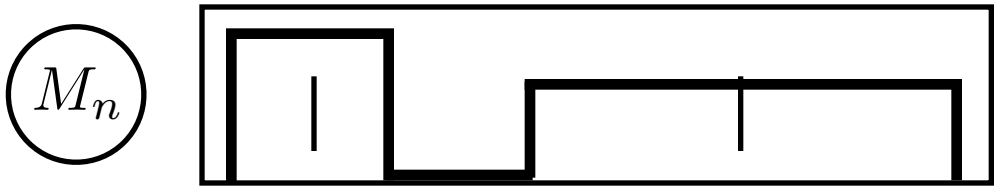


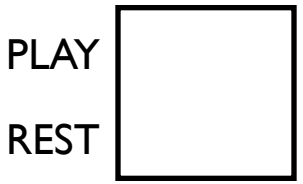


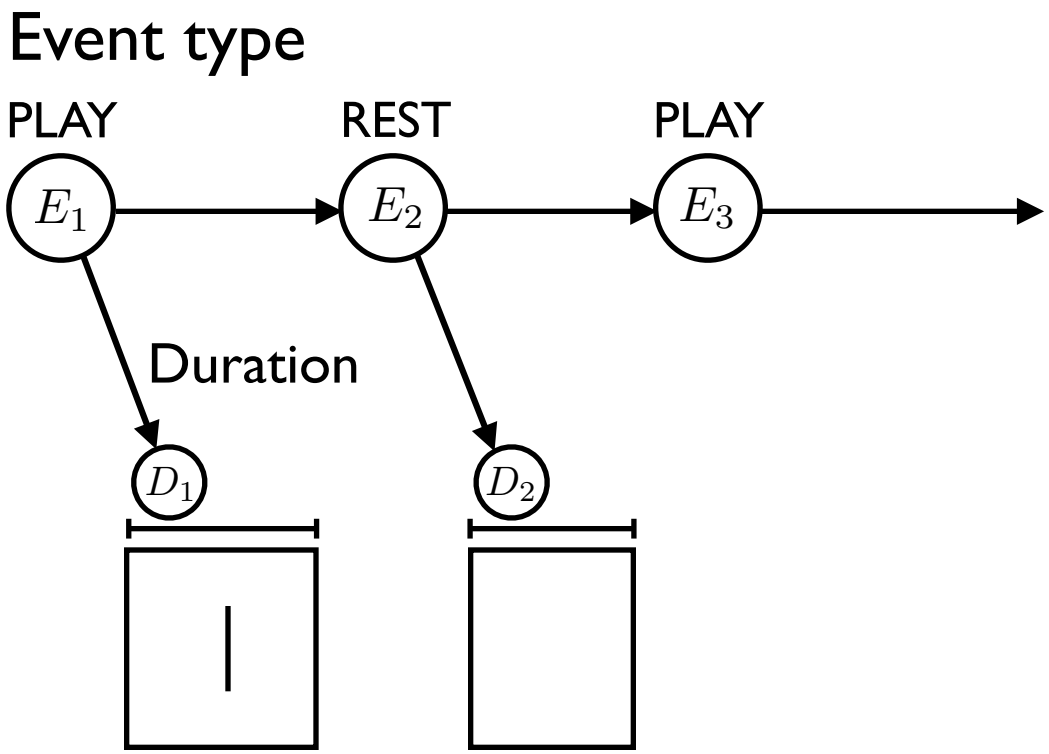

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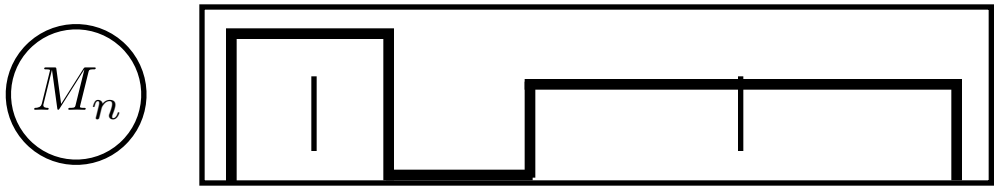


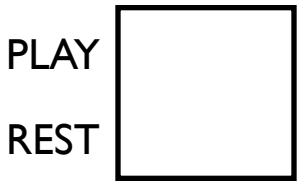


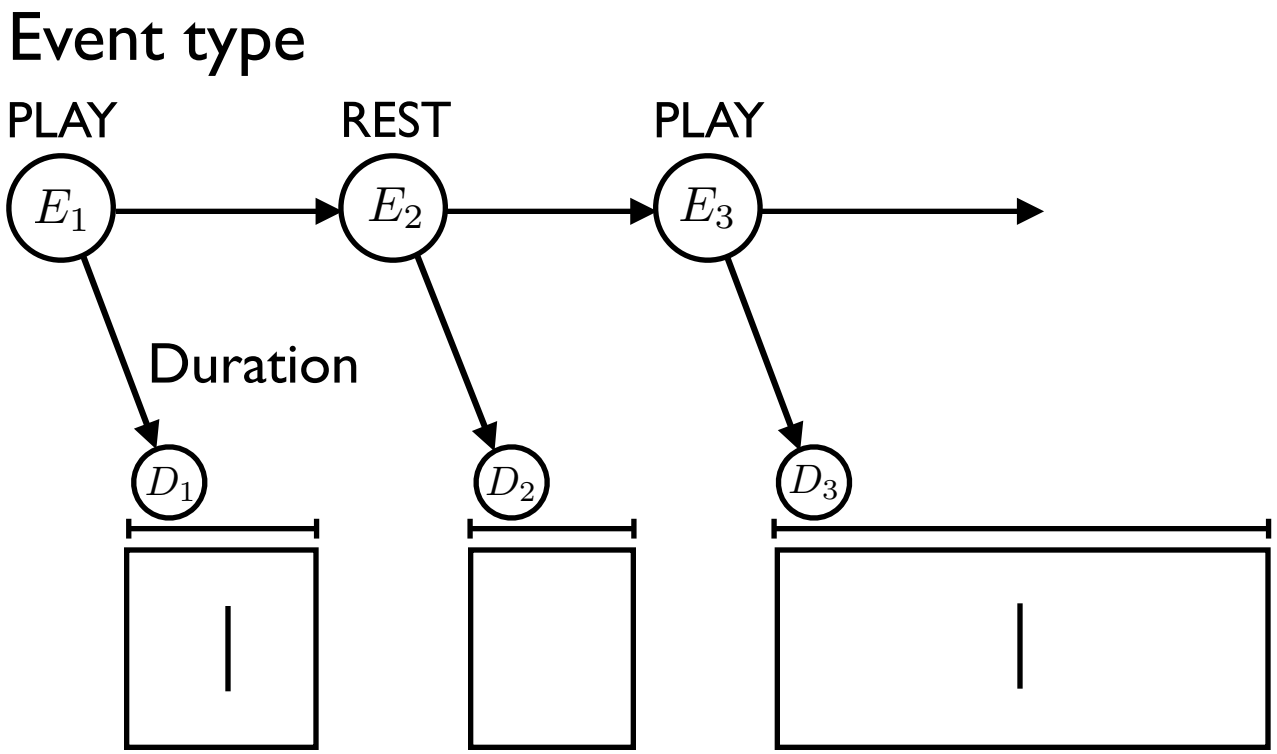

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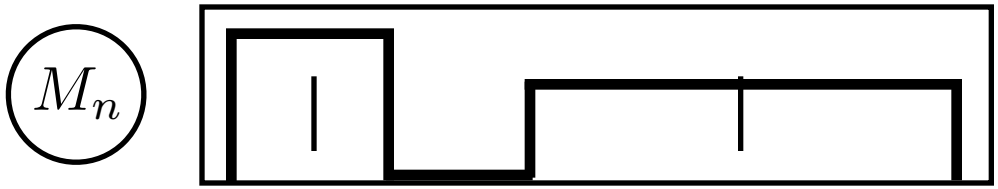


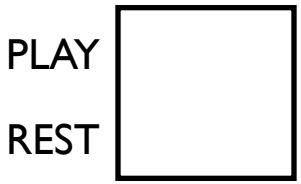



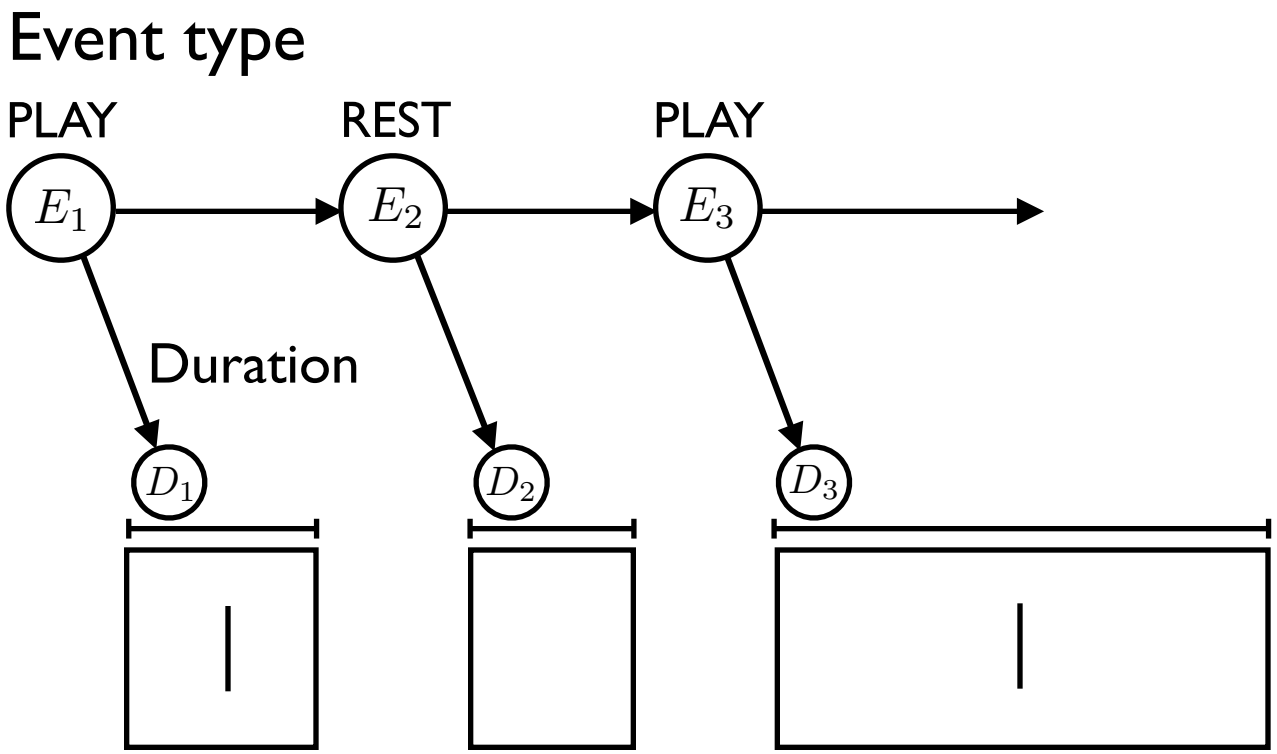

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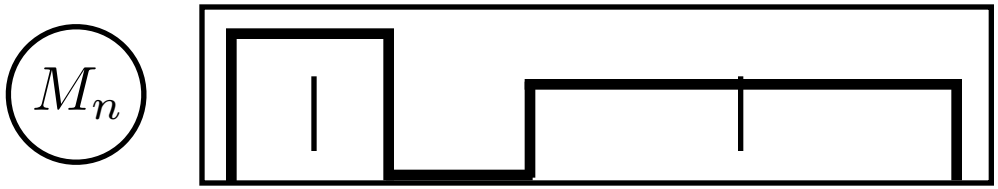


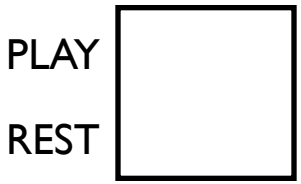



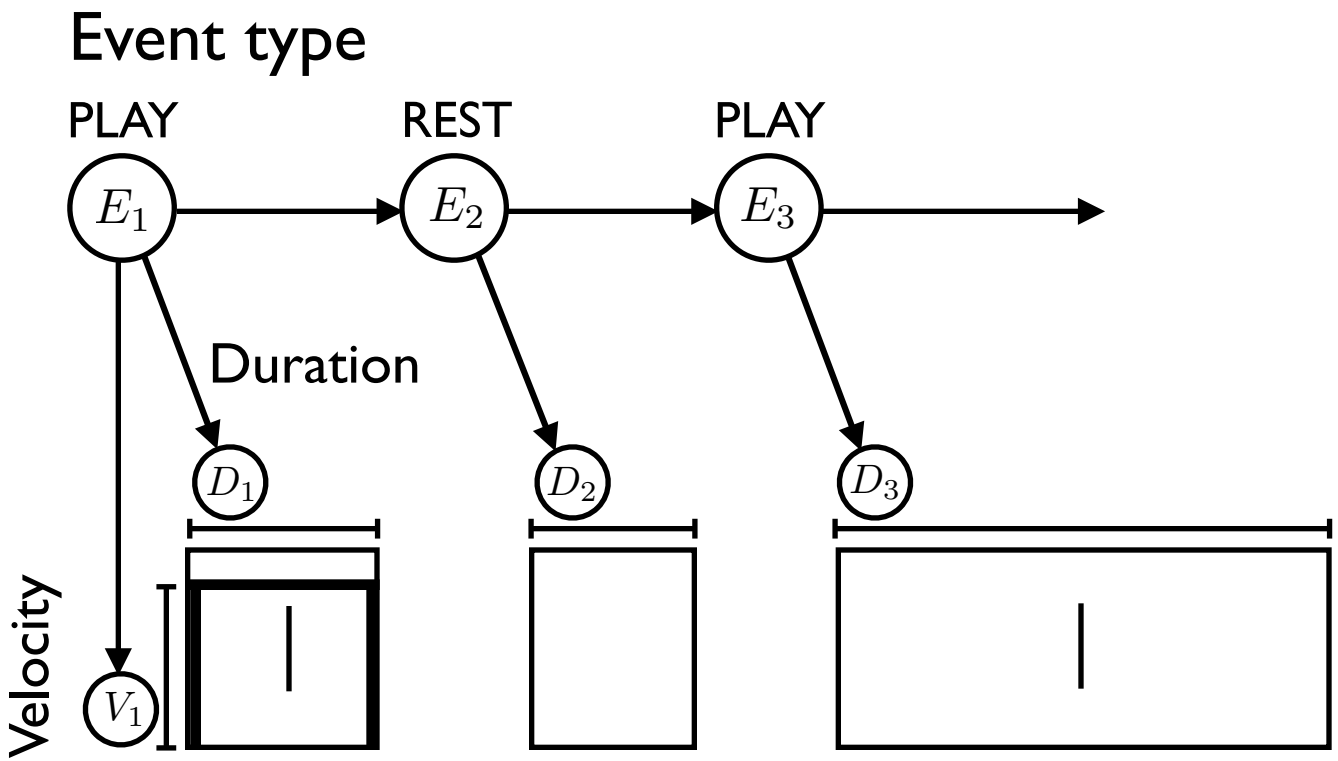

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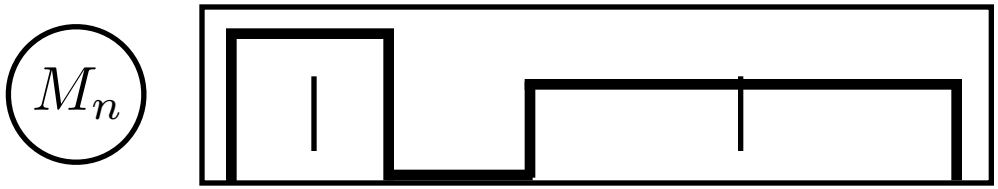


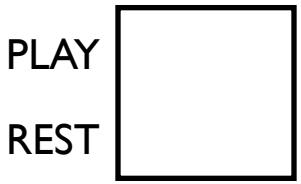



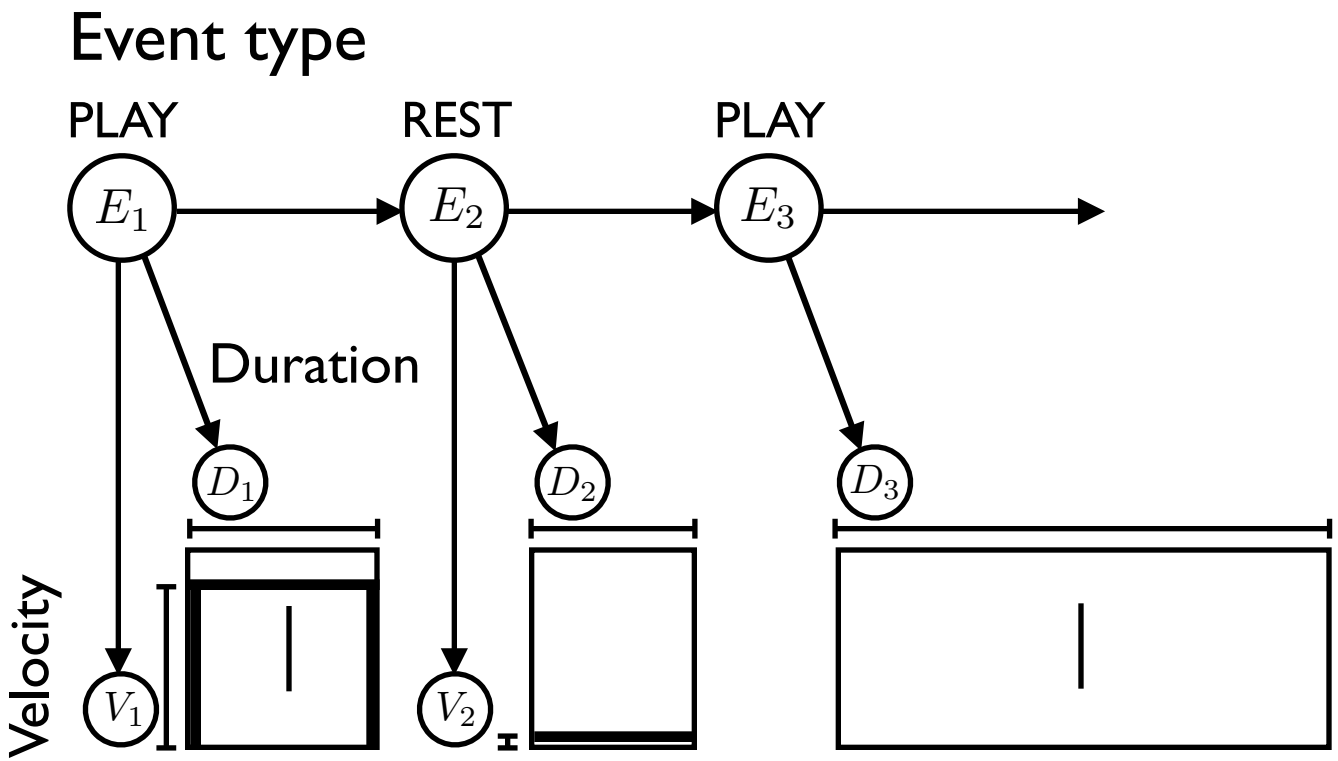

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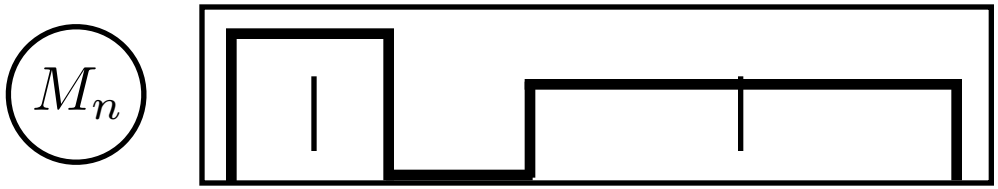


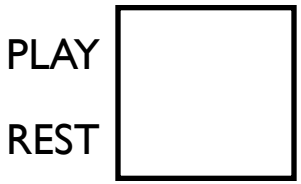



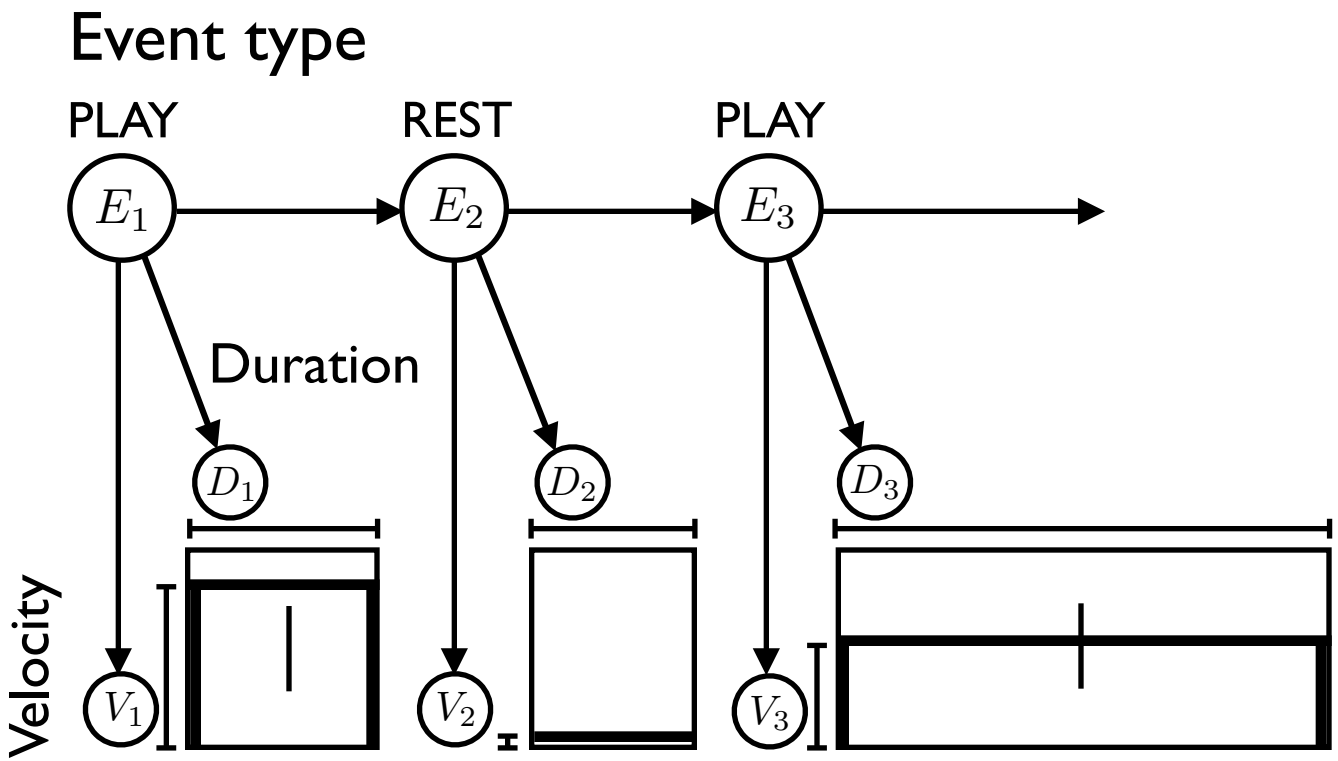

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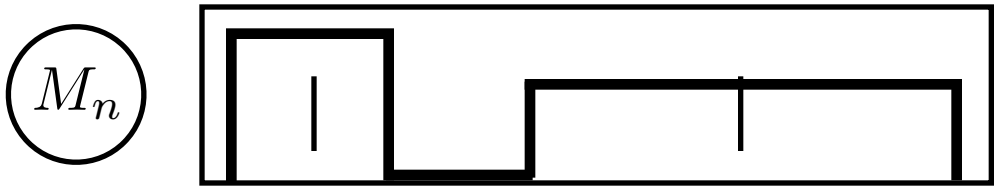


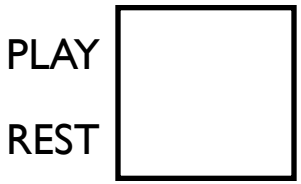


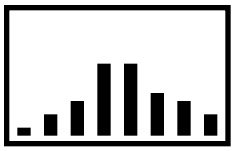


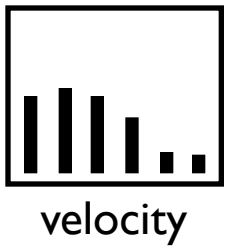


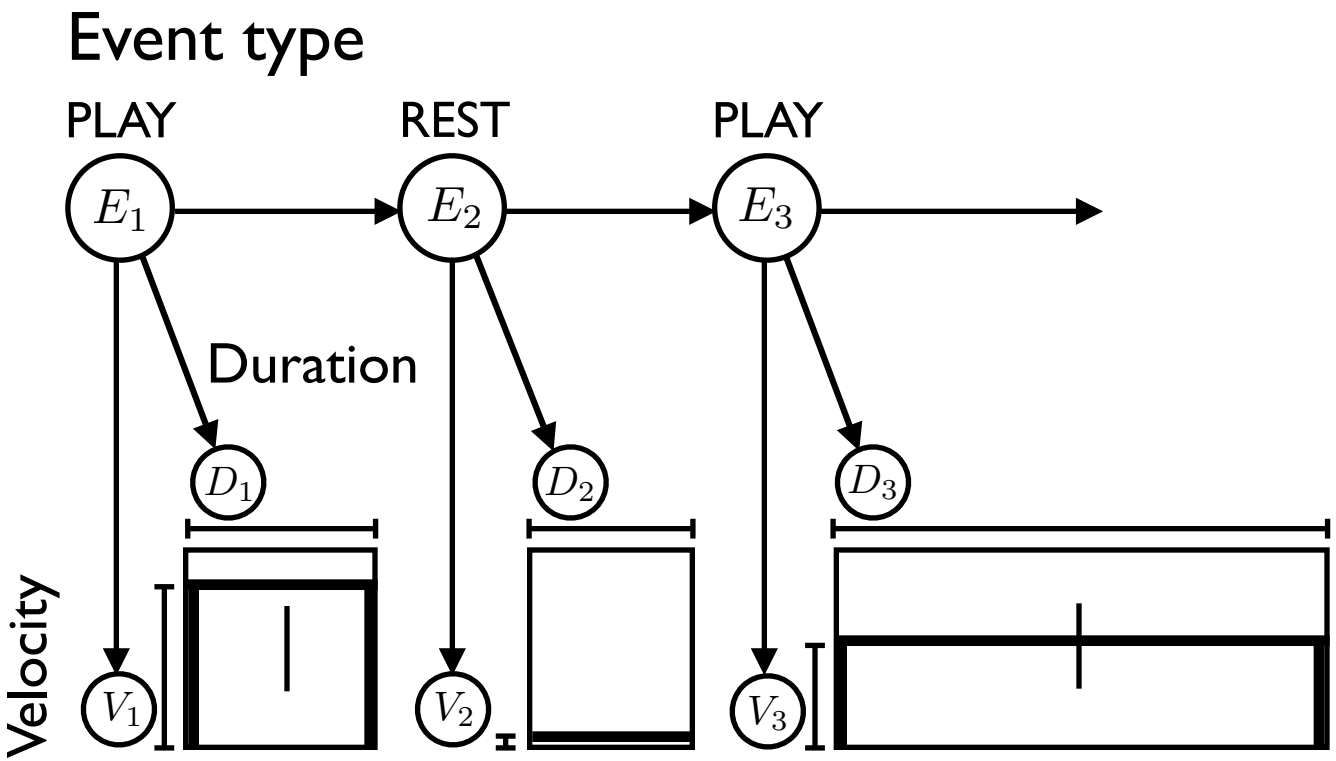

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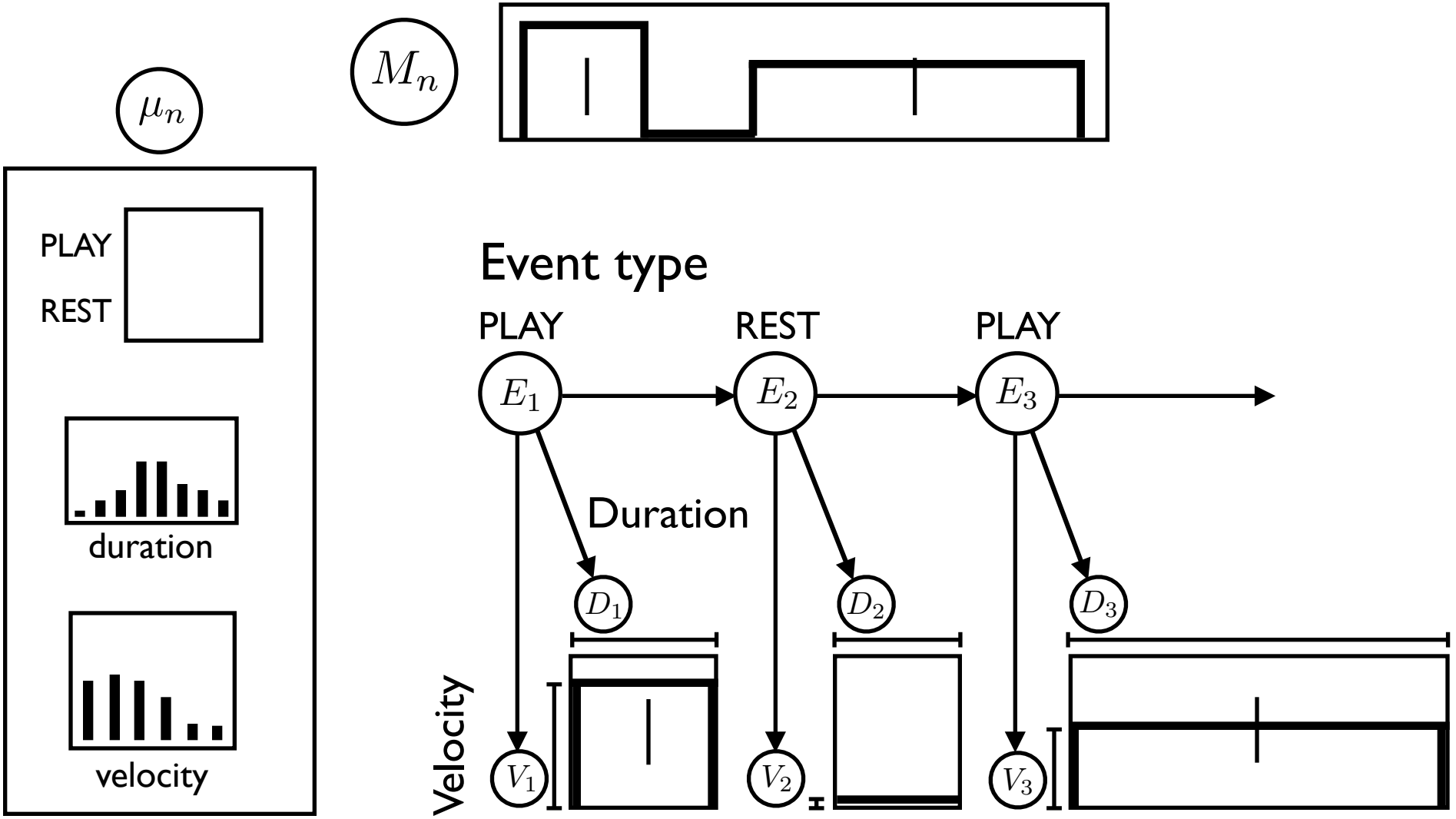

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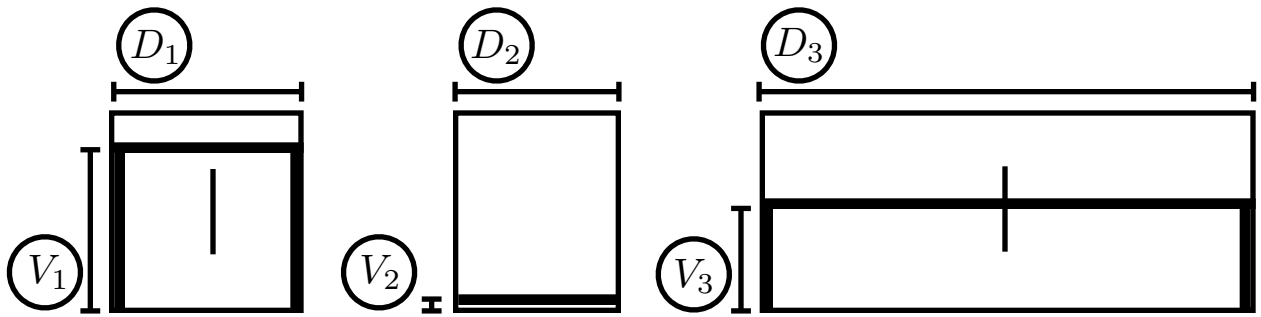
# Activation Model



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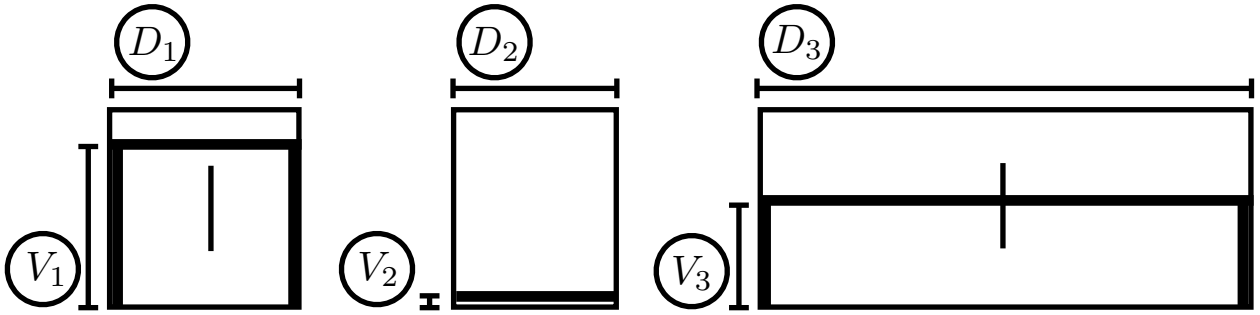

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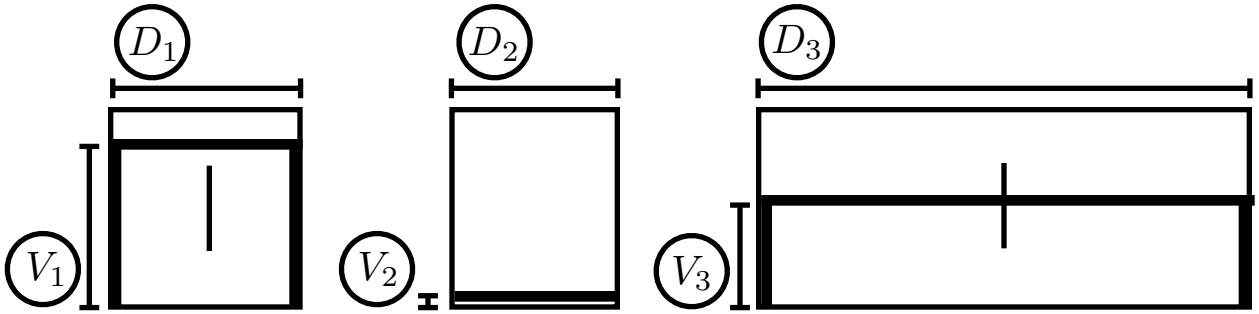

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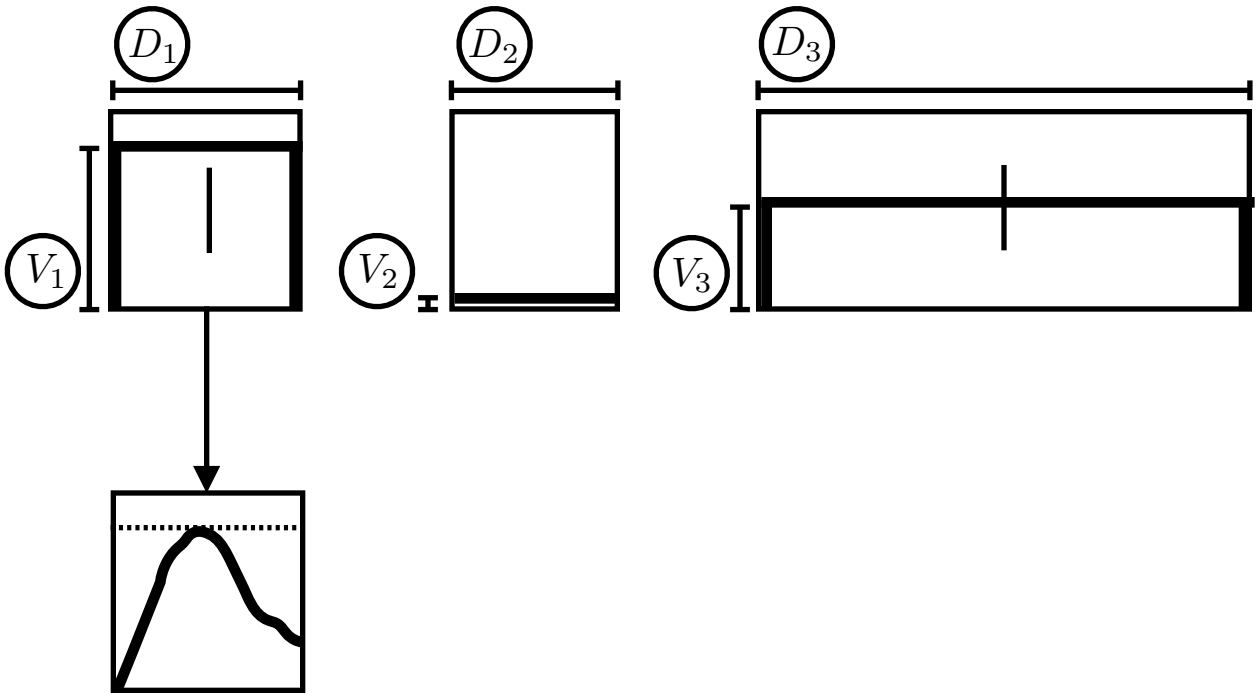

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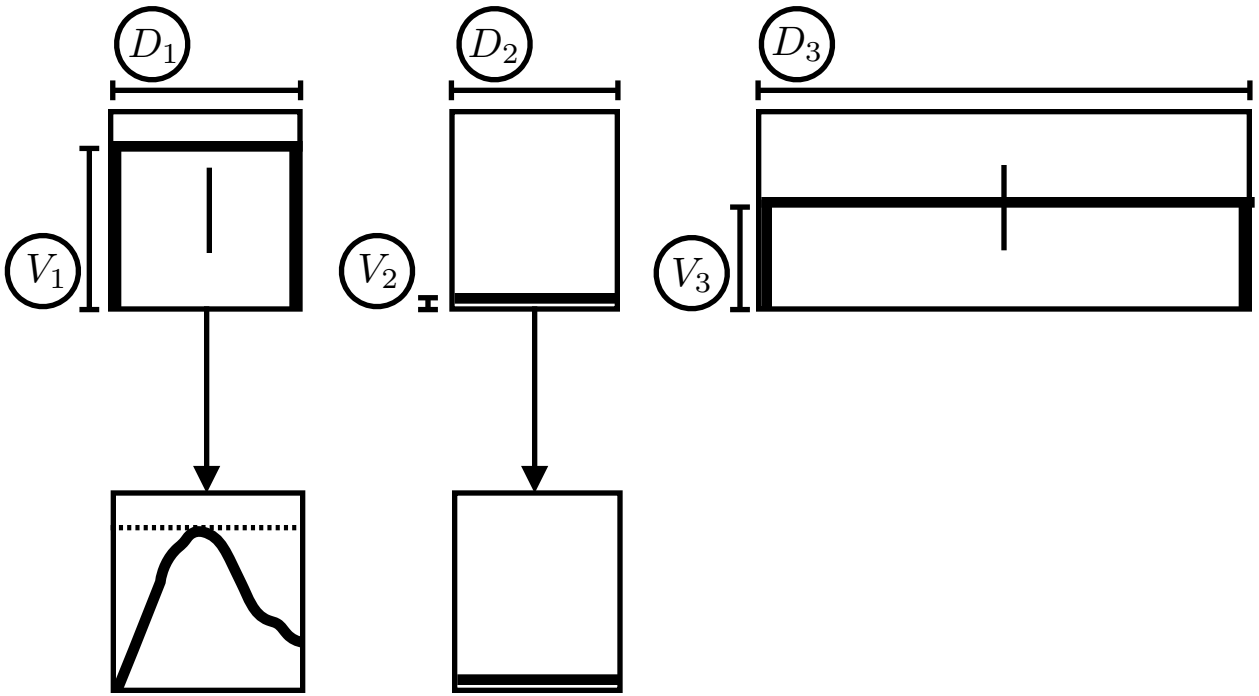

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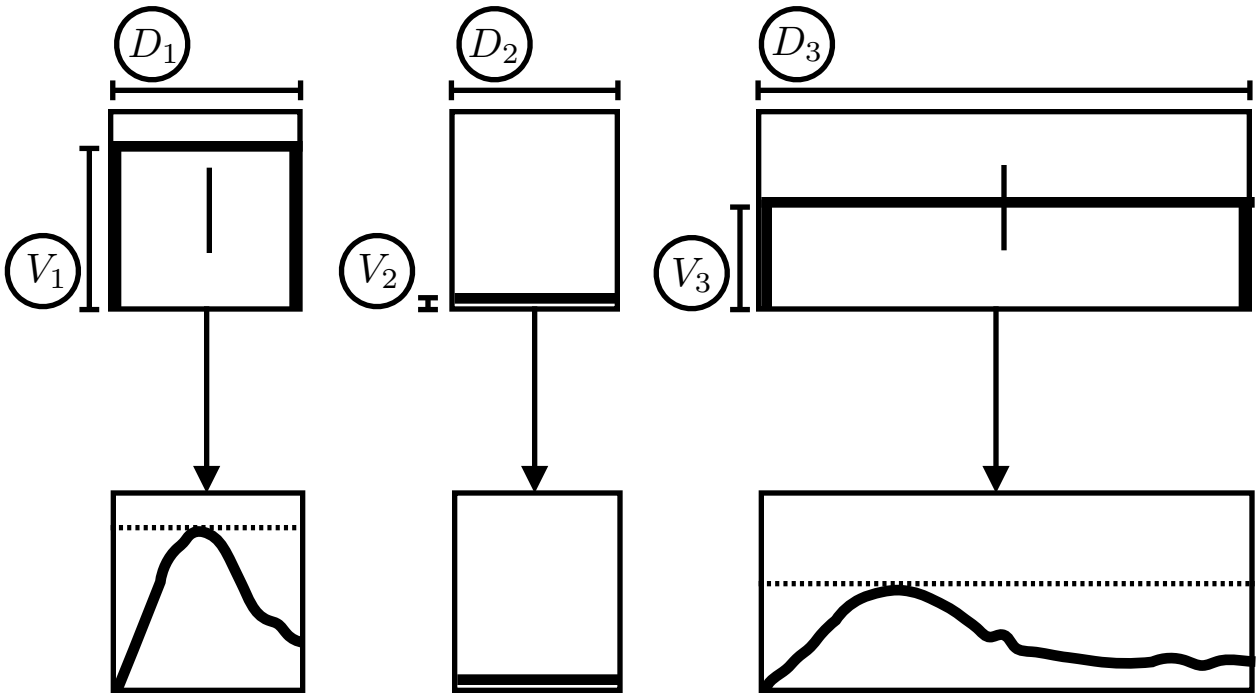

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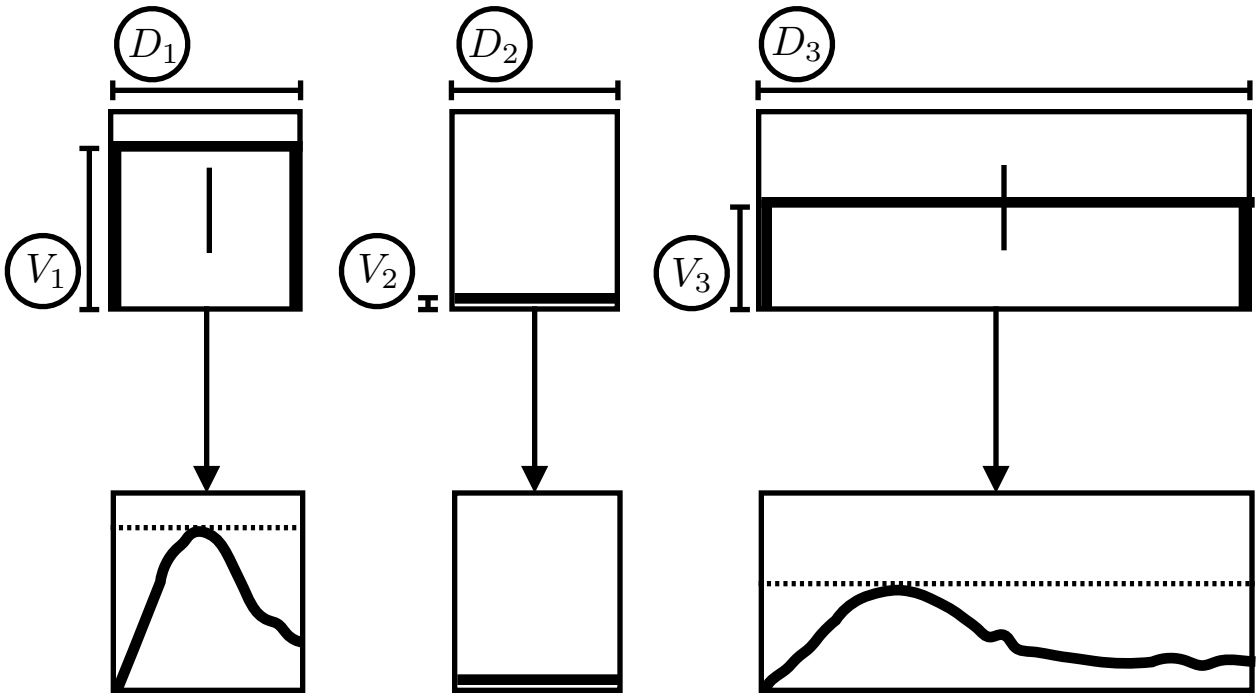


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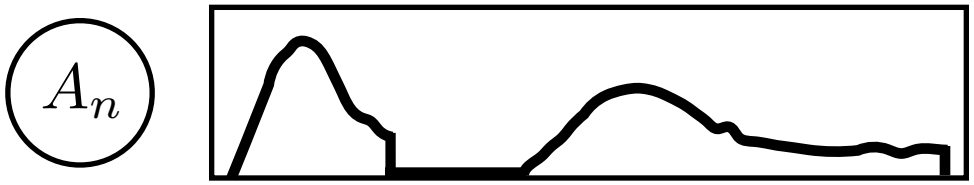

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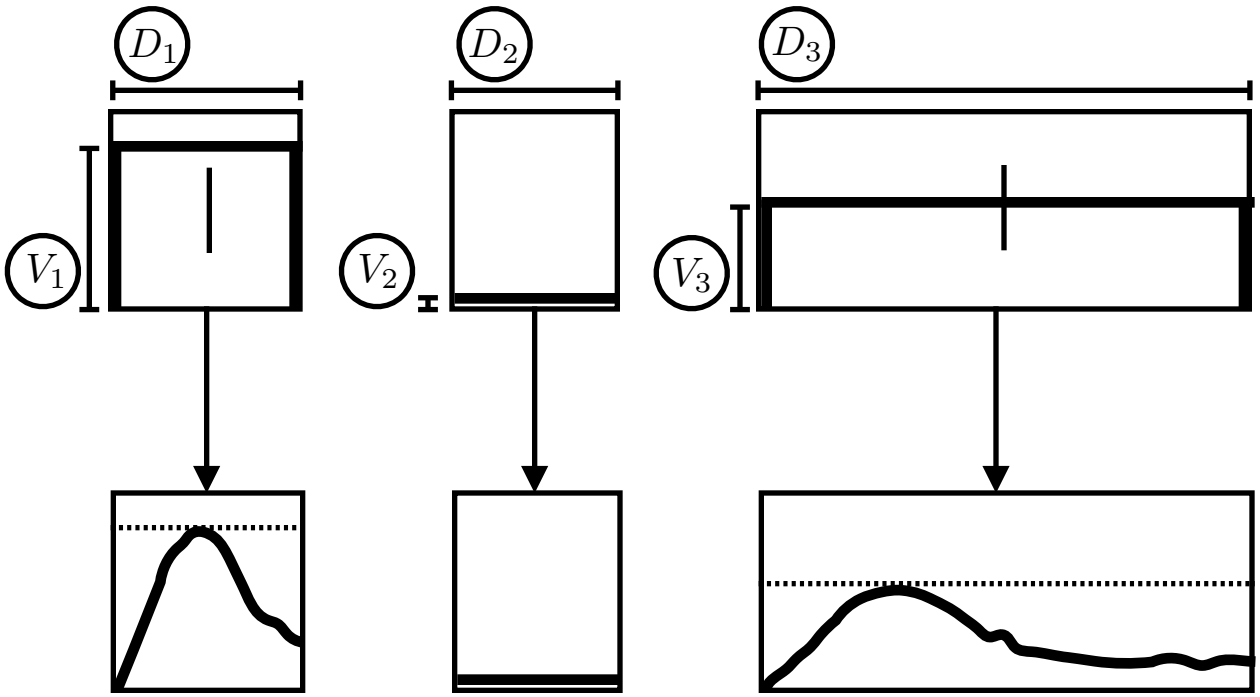


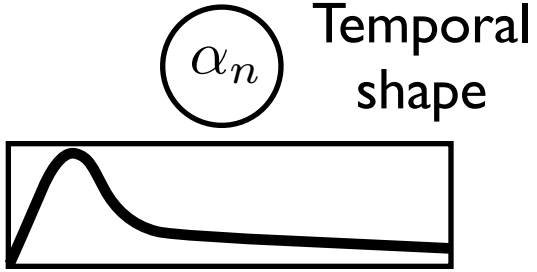


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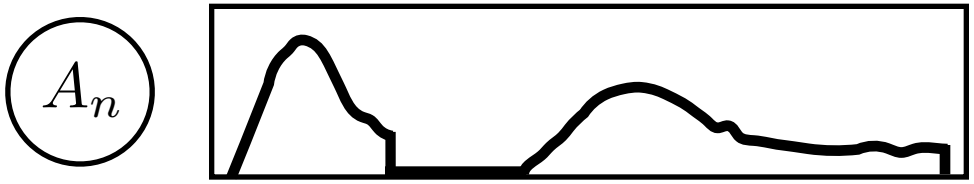

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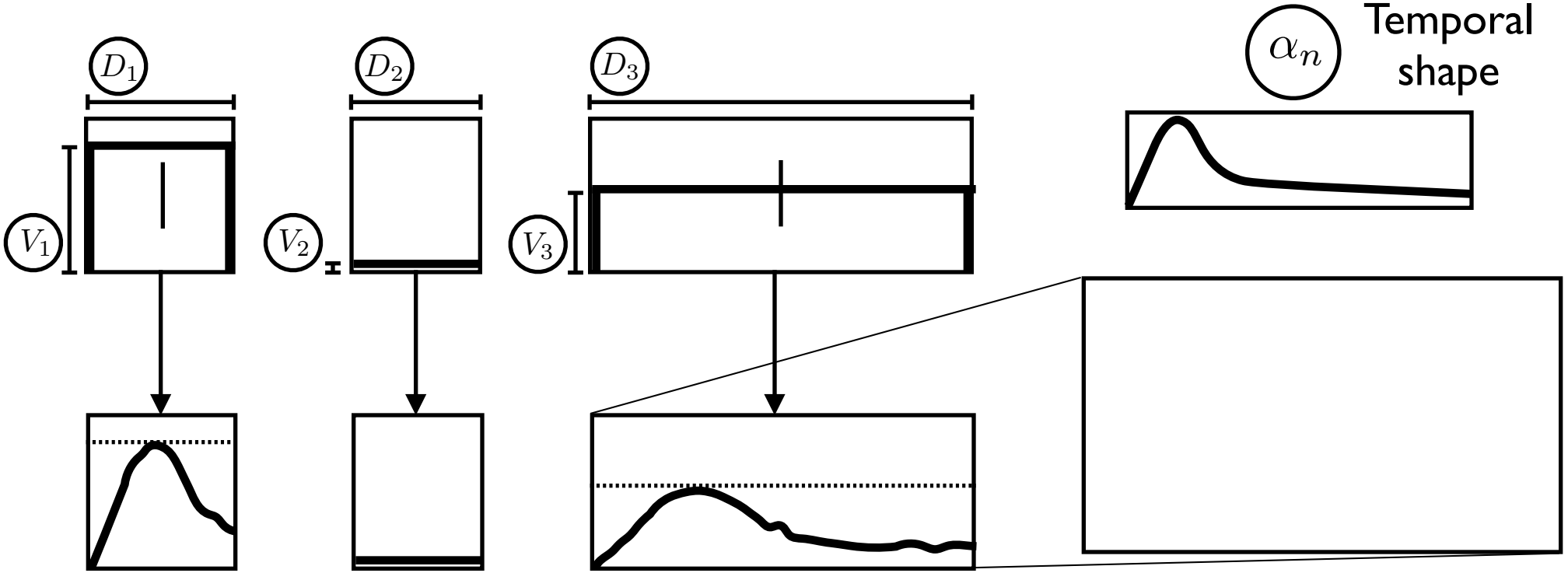


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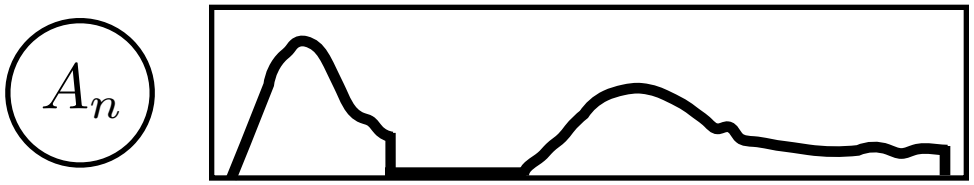

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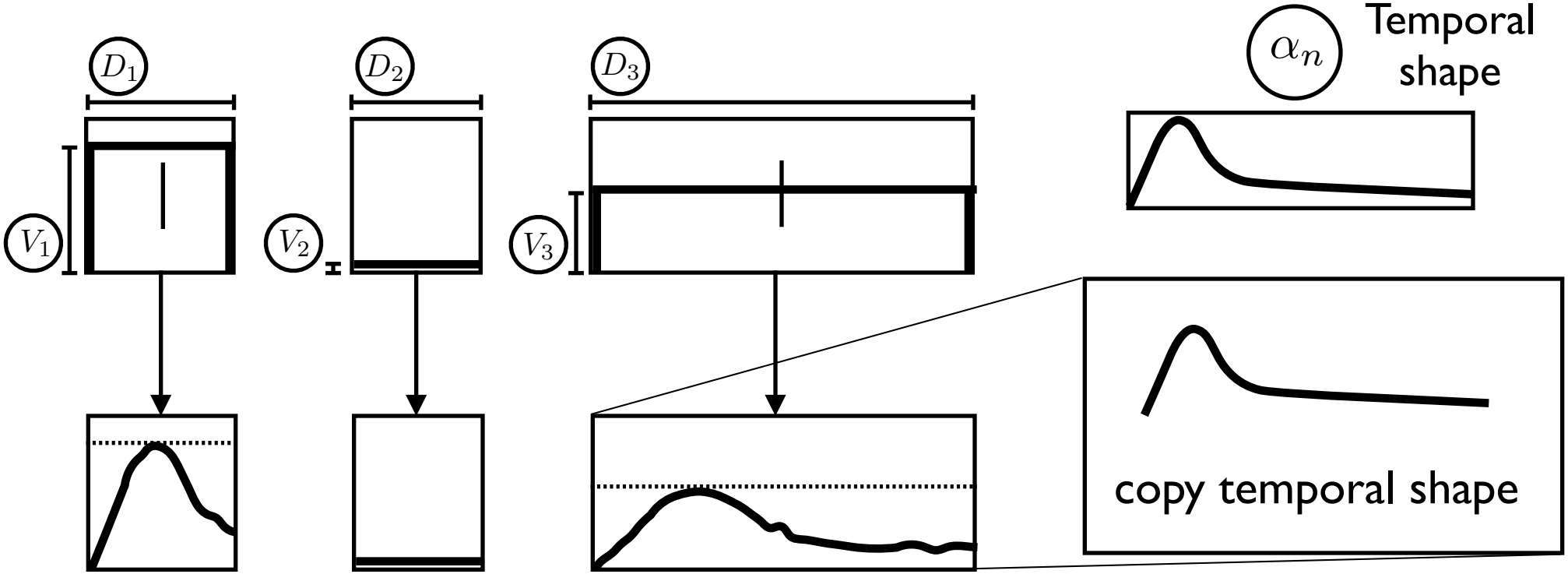


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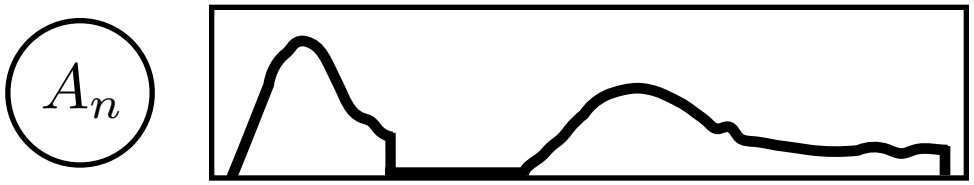

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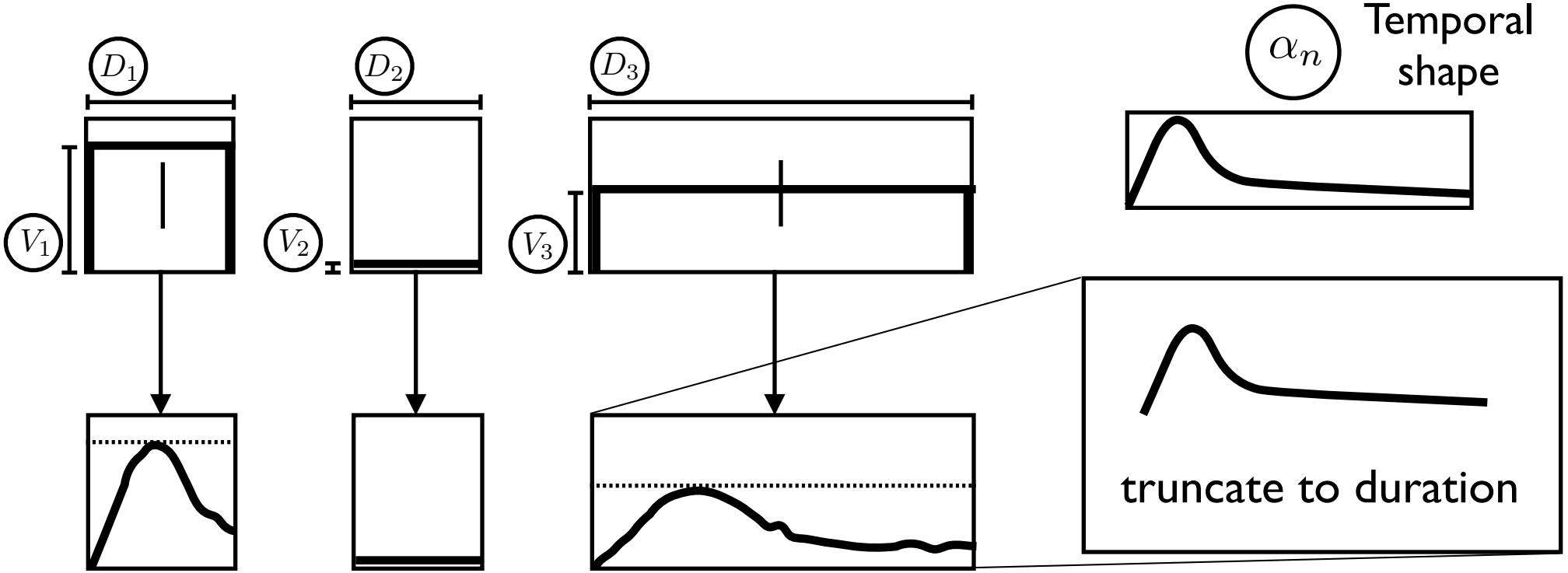


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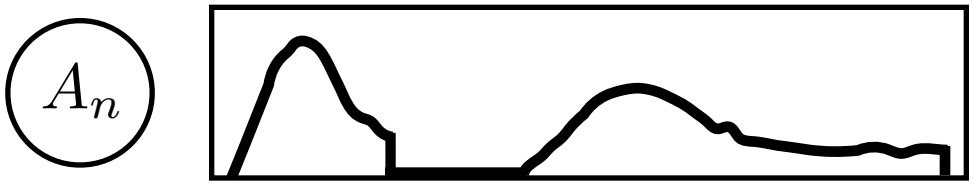

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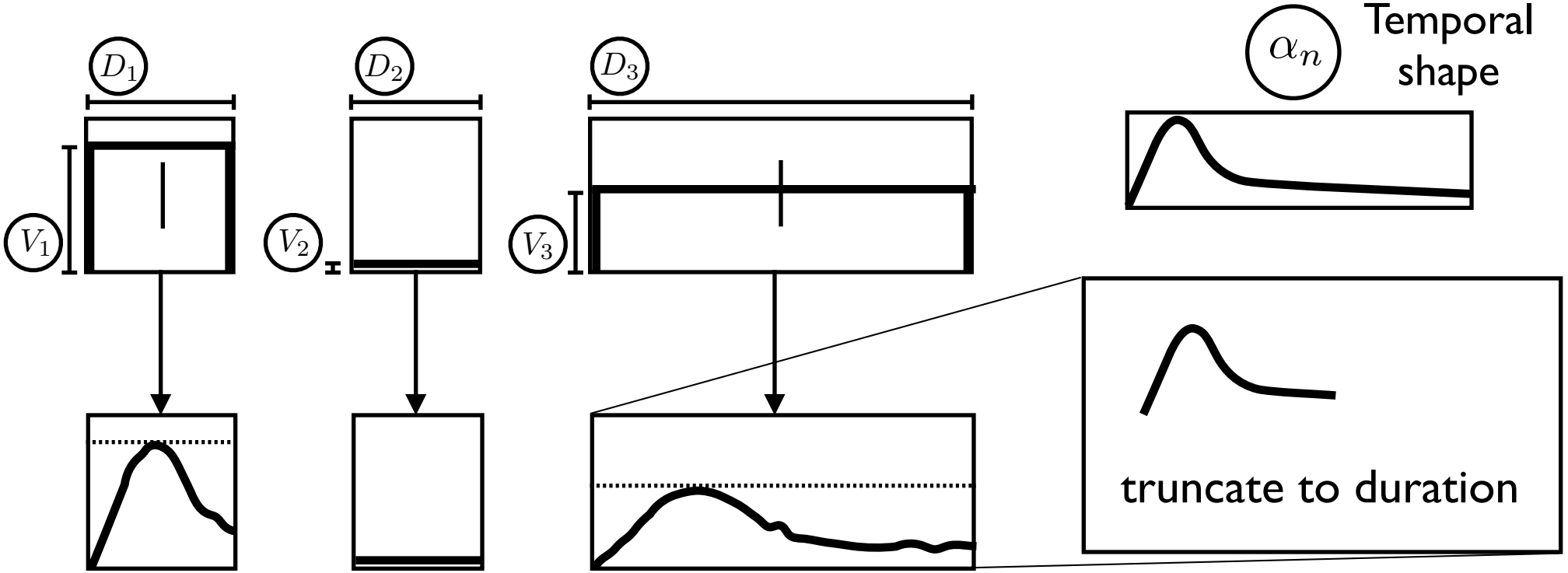


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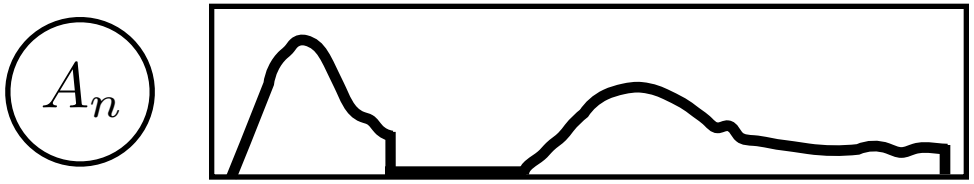

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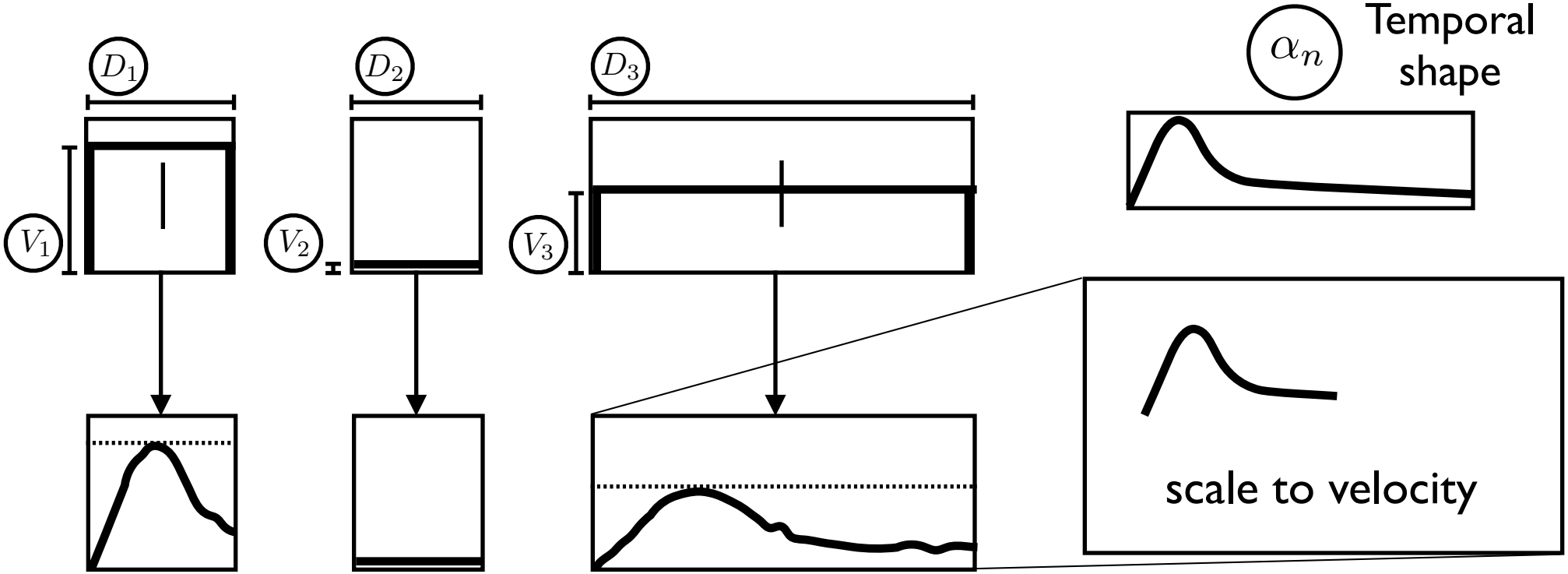


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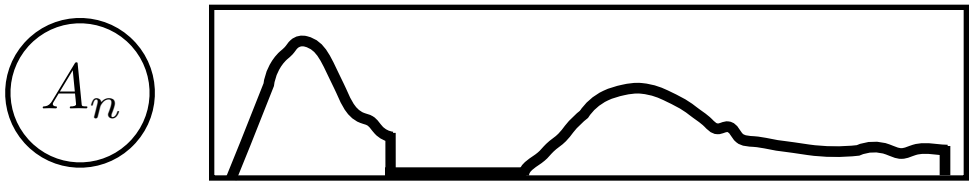

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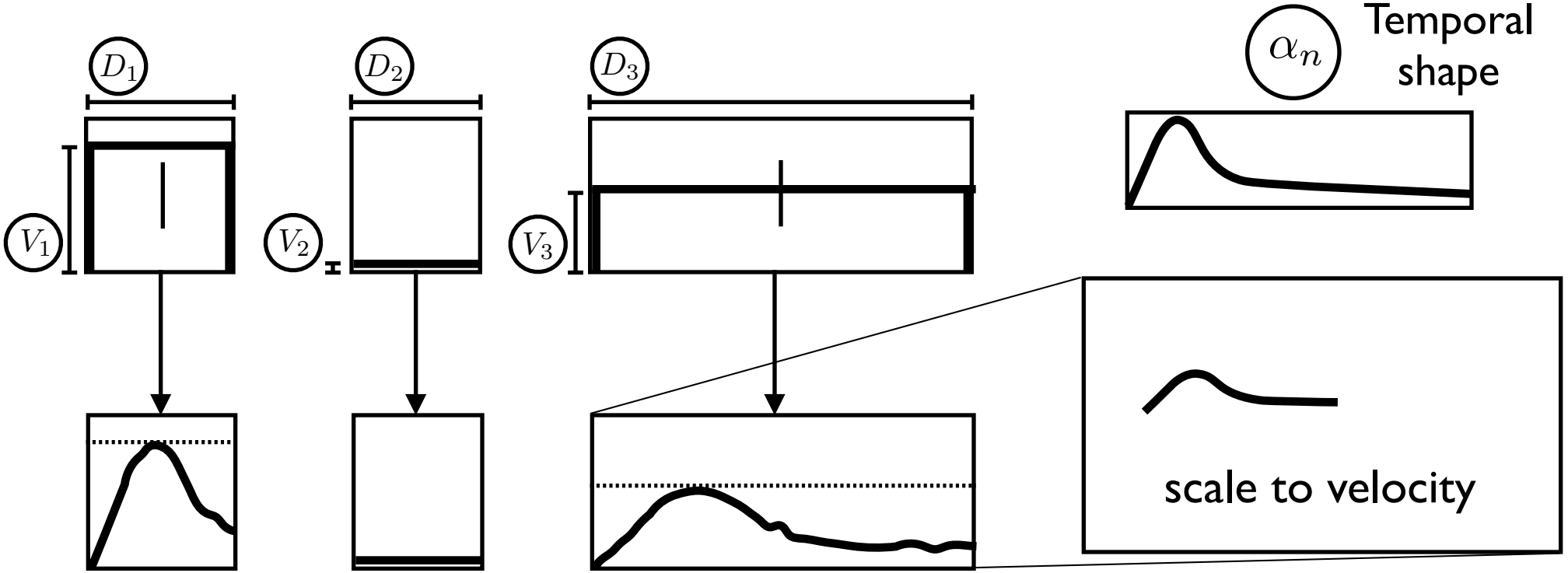


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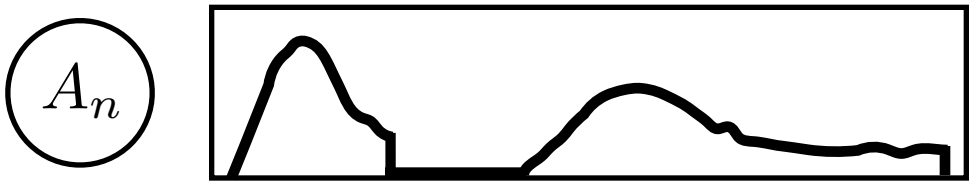

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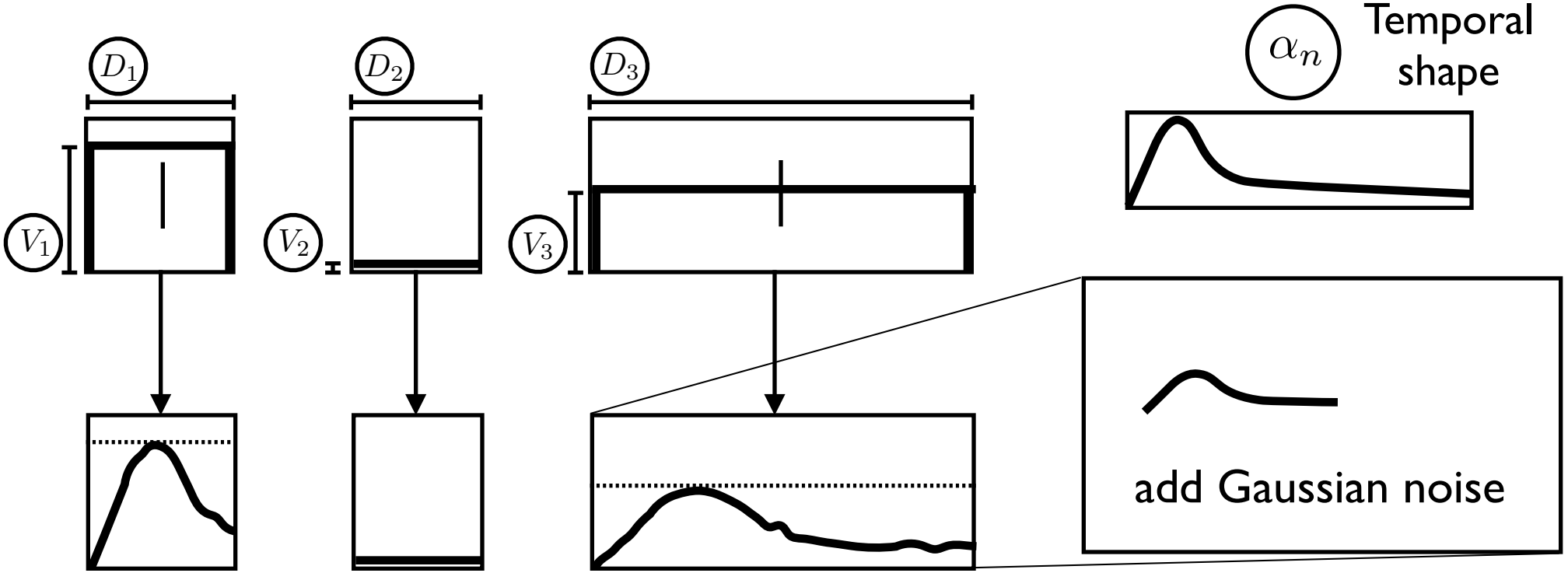
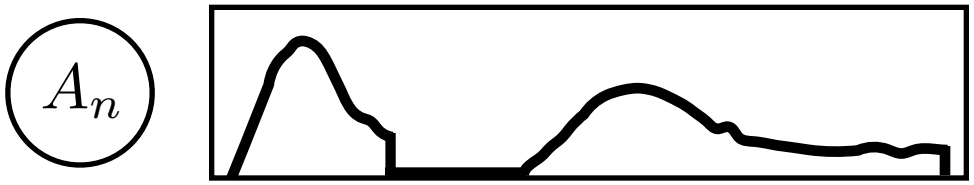
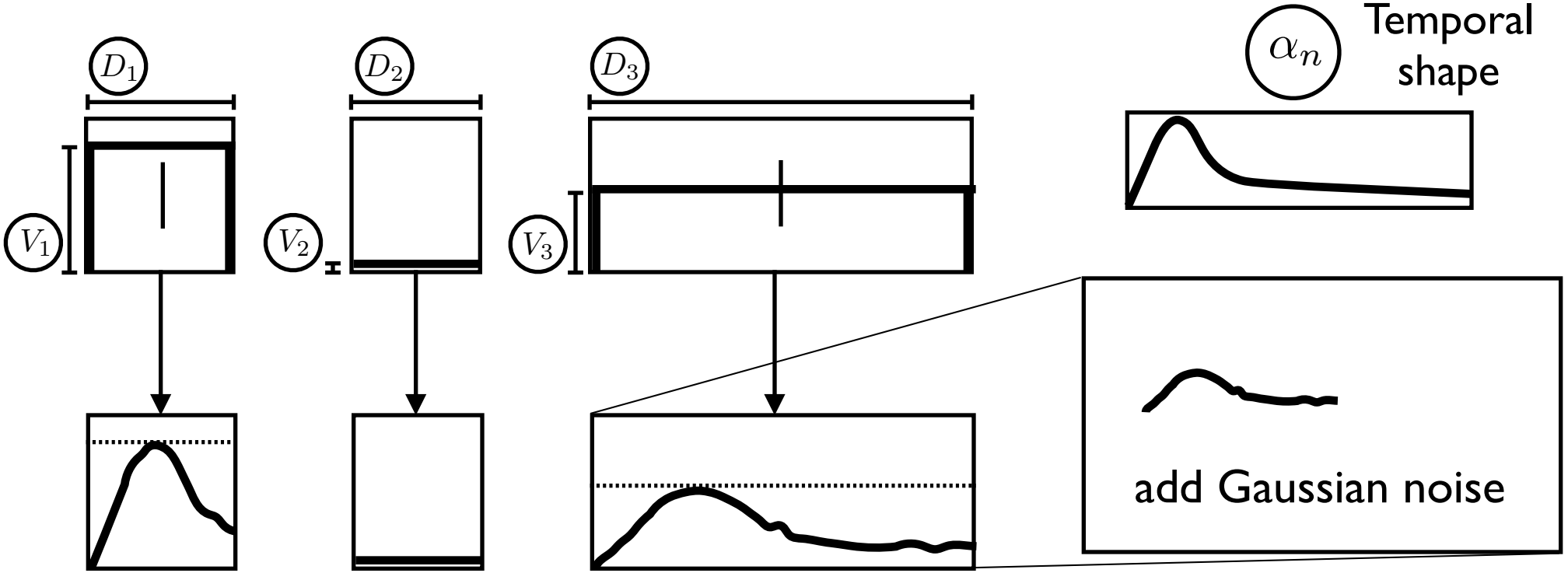
# Activation Model



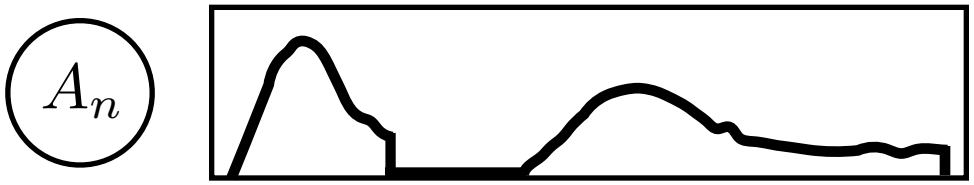

Activation



# Activation Model




Activation



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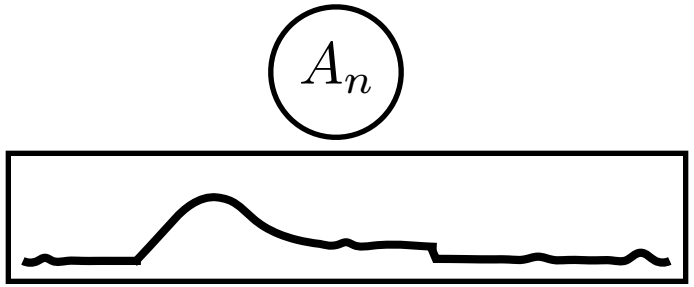
# Component Spectrogram Model

Activation



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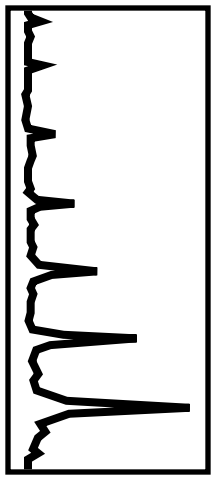
# Component Spectrogram Model

Activation

$A_n$

Spectral shape

$\sigma_n$



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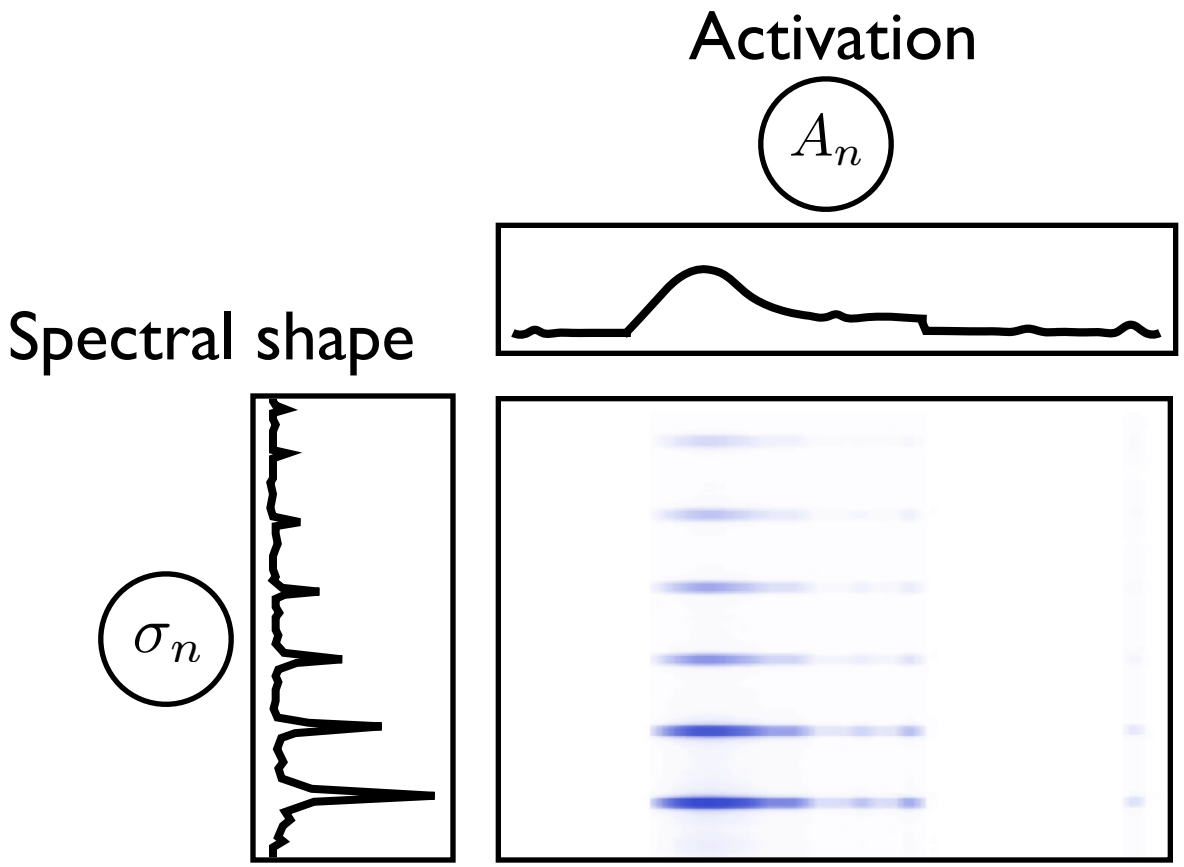
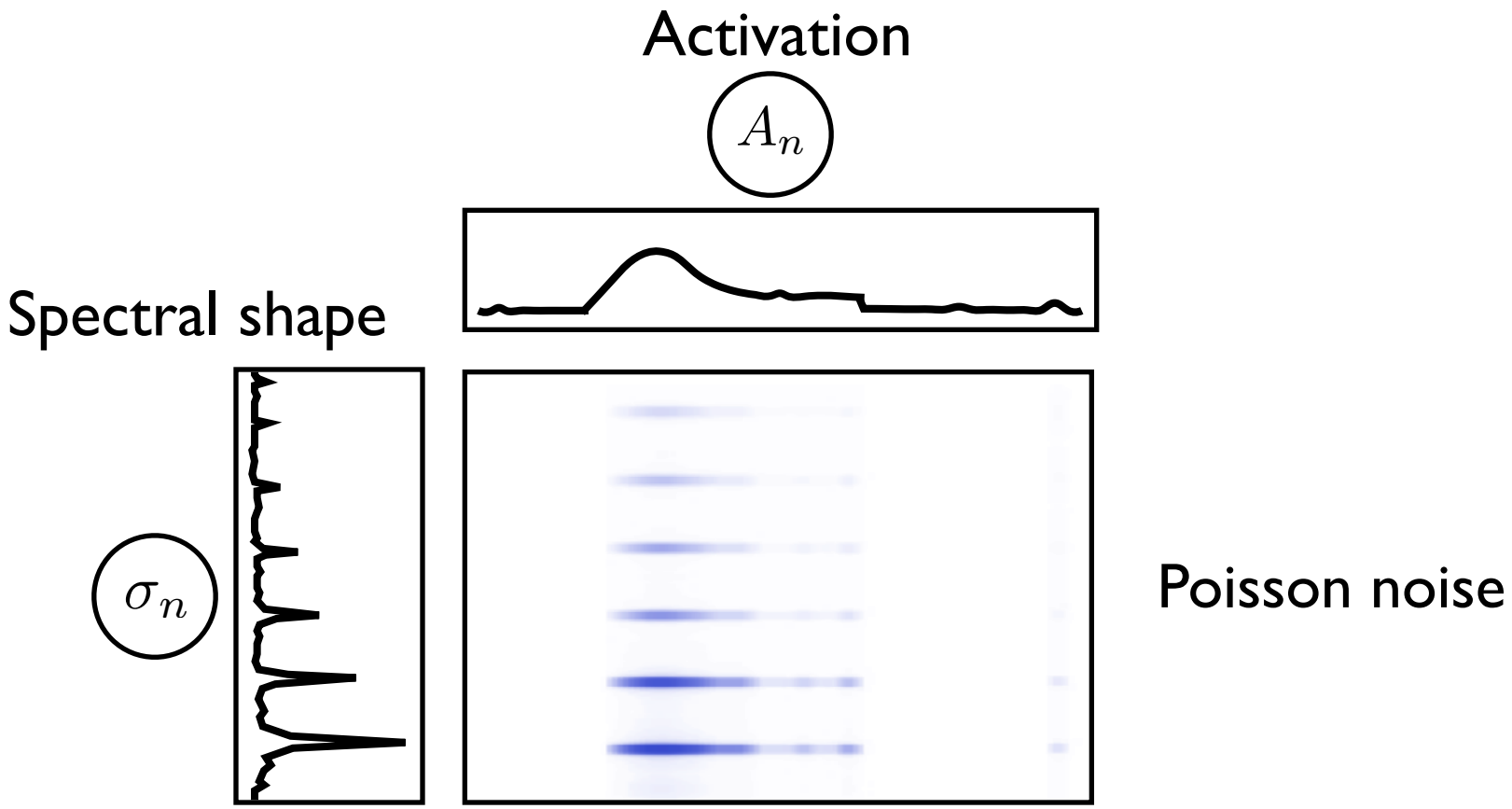
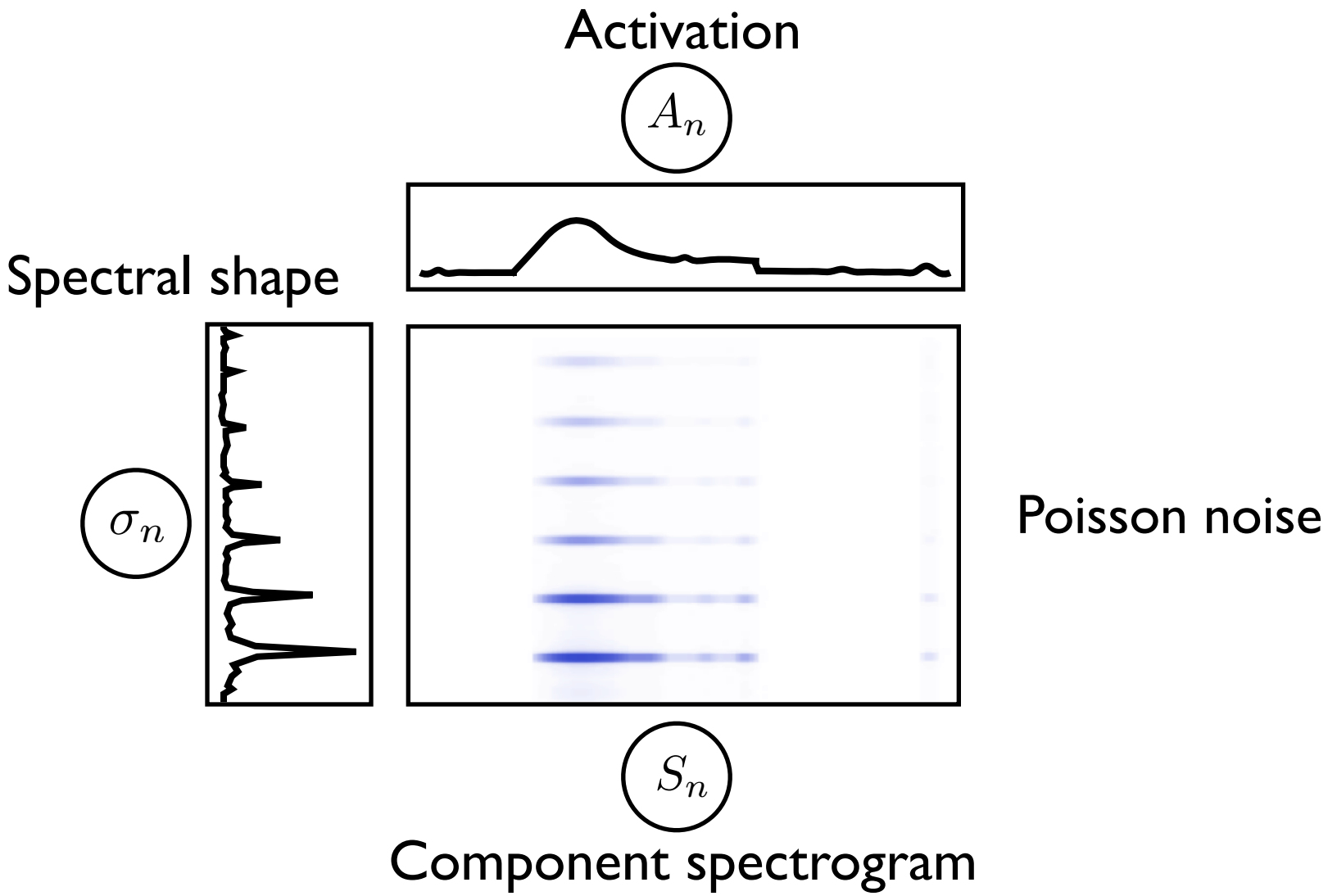
# Component Spectrogram Model



# Component Spectrogram Model



# Component Spectrogram Model



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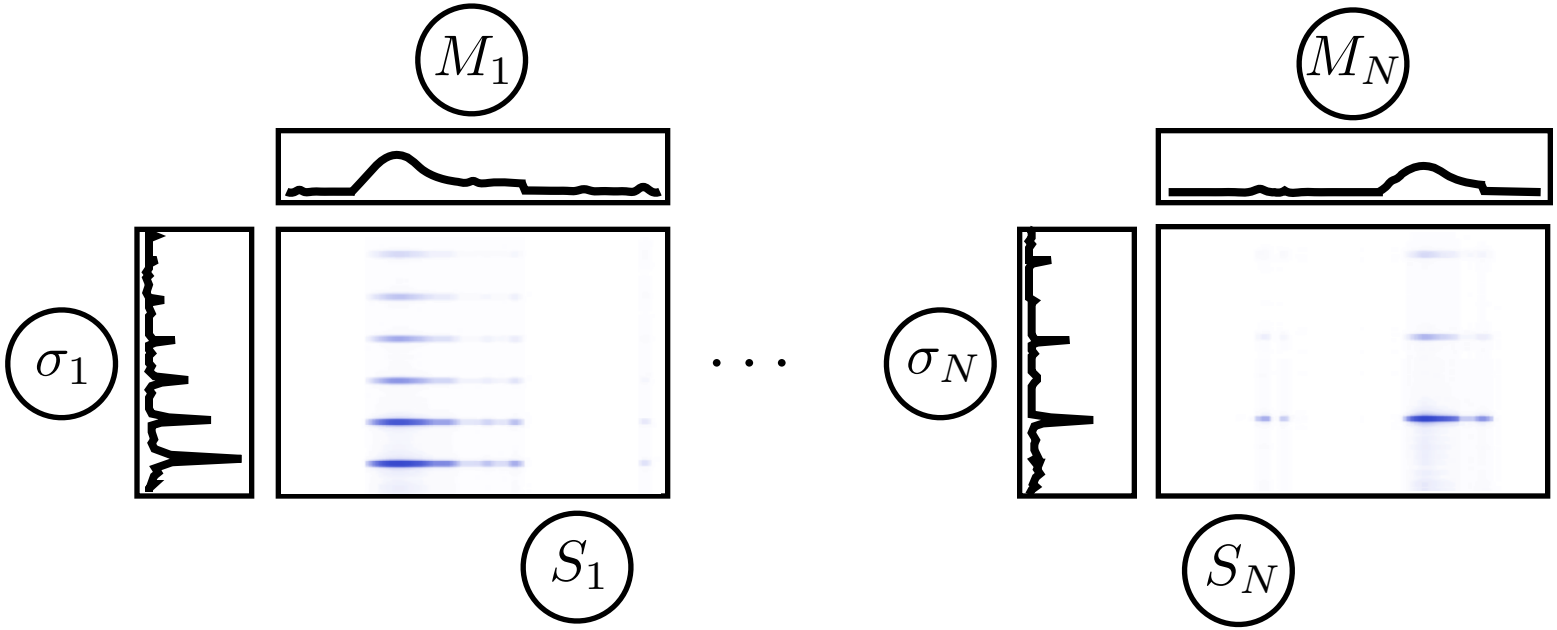
# Total Spectrogram Model



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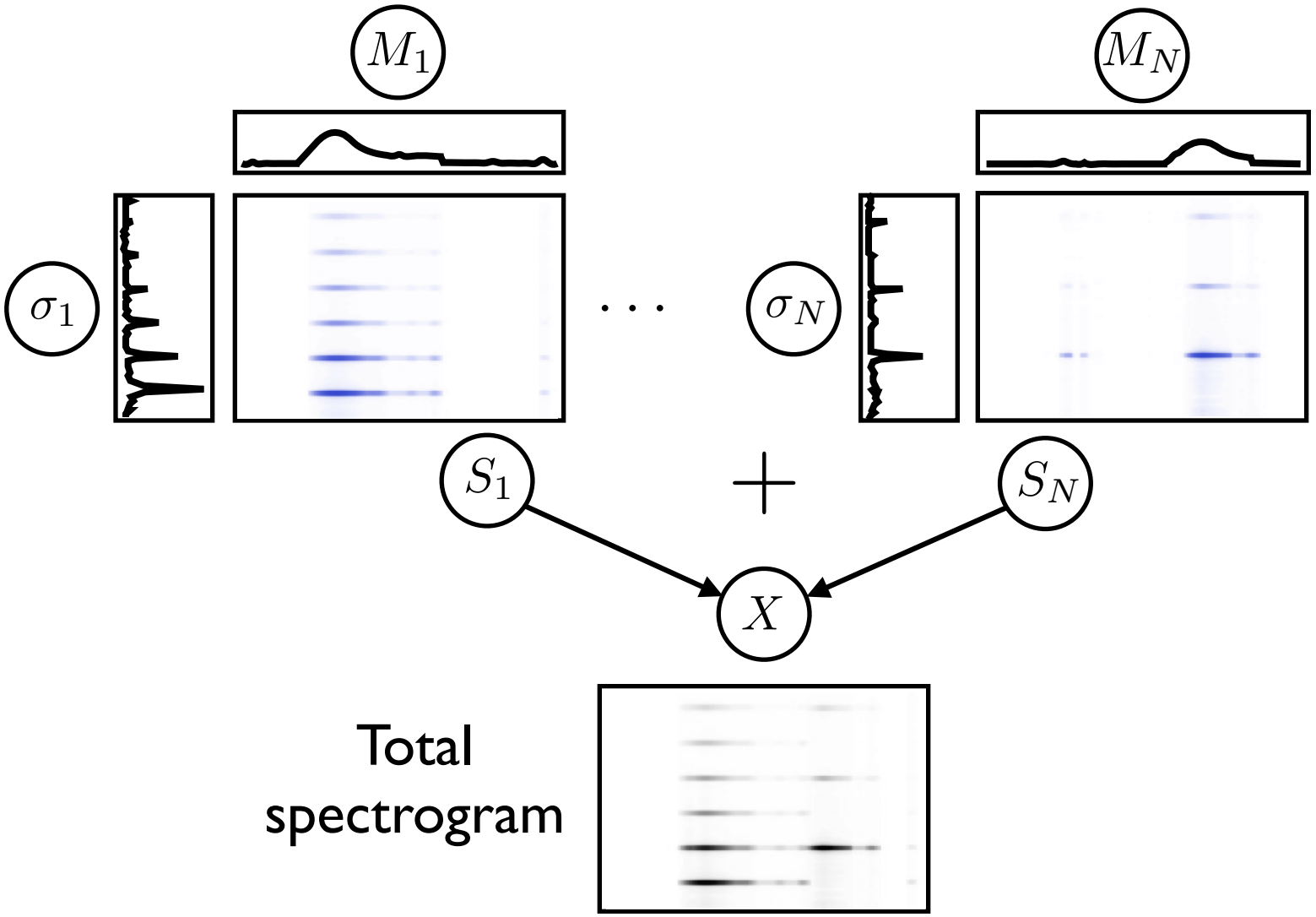
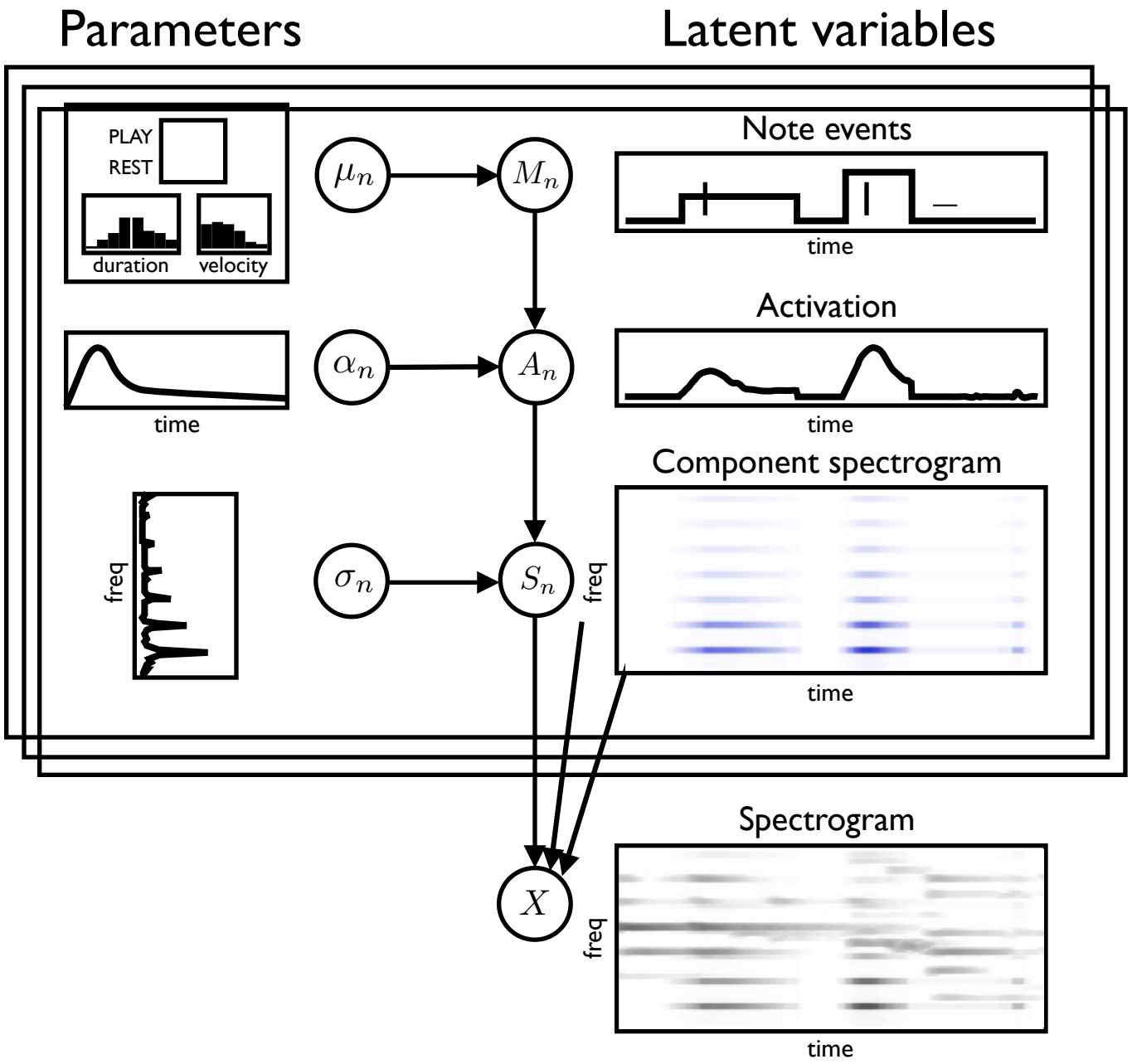
# Total Spectrogram Model



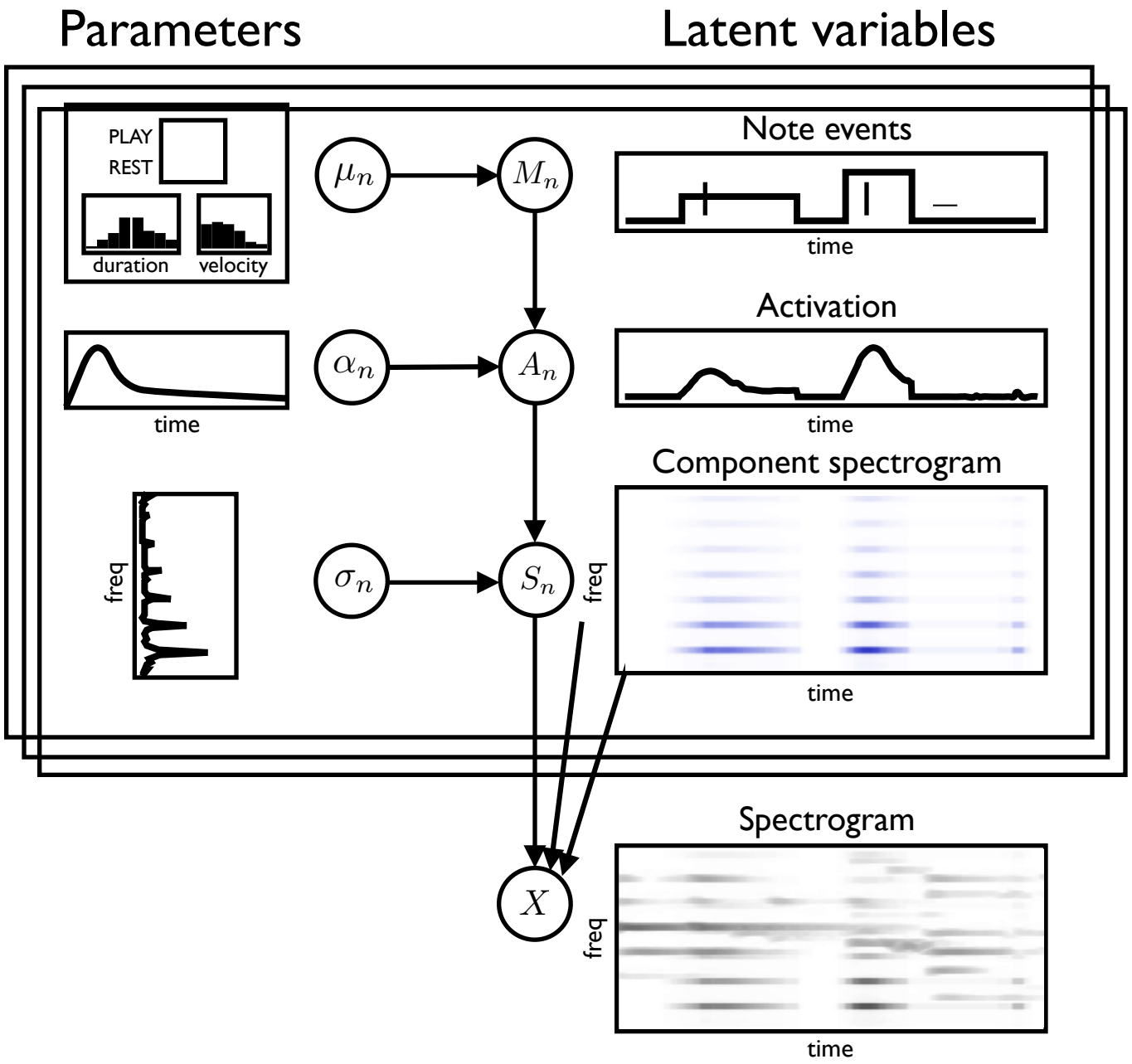
Berkeley NLP

# Learning and Inference



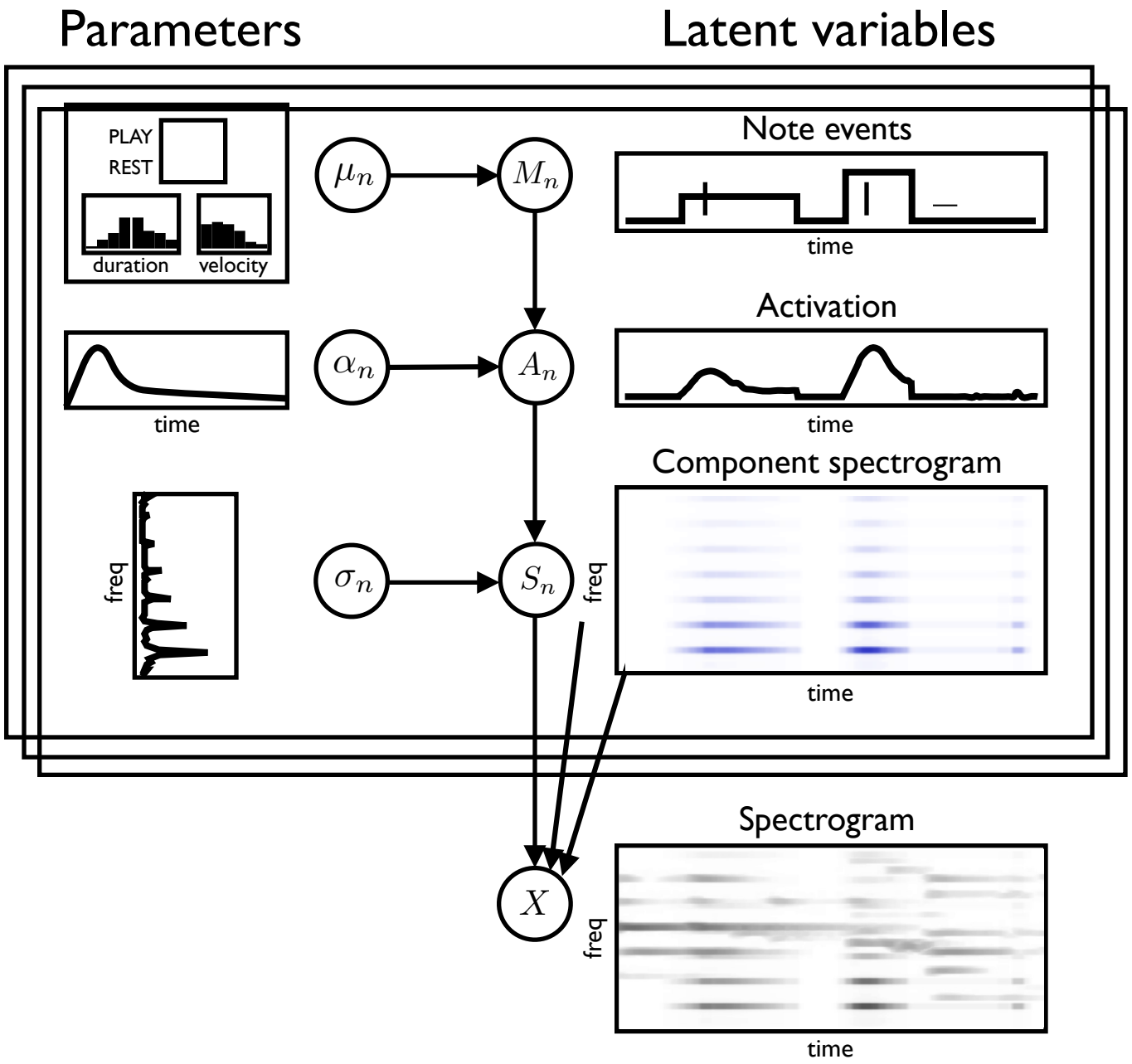
Berkeley NLP

# Learning and Inference



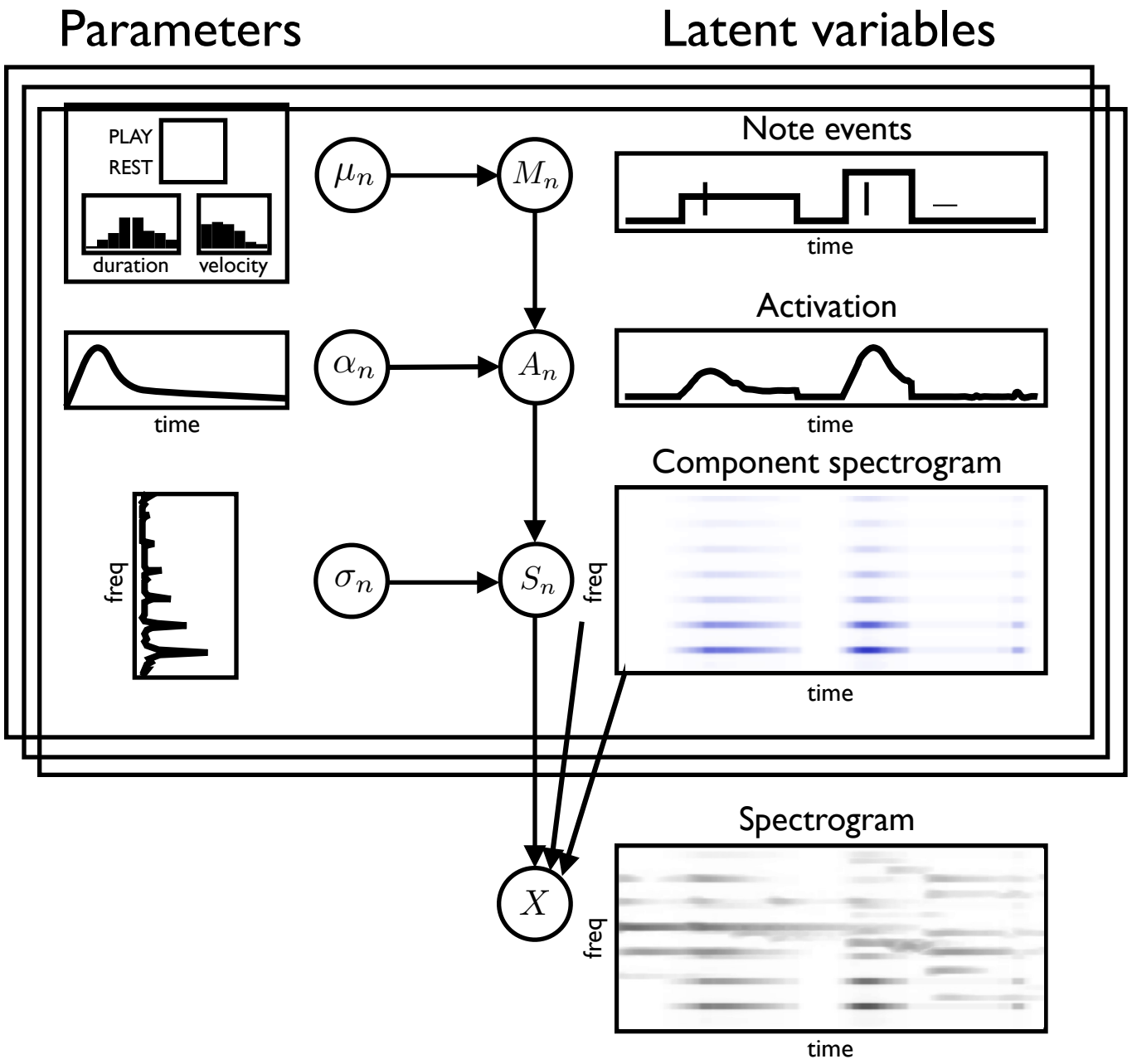
Berkeley NLP

# Learning and Inference



Berkeley NLP

# Learning and Inference




# Learning and Inference

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# Learning and Inference

Note events update:

$$M|A, \alpha, \mu$$

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# Learning and Inference

Note events update:

$$M|A, \alpha, \mu$$

Semi-Markov dynamic program

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# Learning and Inference

Note events update:

$$M|A, \alpha, \mu$$

Semi-Markov dynamic program

Temporal shapes update:

$$\alpha|A, M$$

Berkeley
N L P

# Learning and Inference

Note events update:

$M|A, \alpha, \mu$

Semi-Markov dynamic program

Temporal shapes update:

$\alpha|A, M$

Closed form update

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N L P

# Learning and Inference

Note events update:

$$M|A, \alpha, \mu$$

Semi-Markov dynamic program

Temporal shapes update:

$$\alpha|A, M$$

Closed form update

Activations update:

$$A|M, X, \alpha, \sigma$$

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N L P

# Learning and Inference

Note events update:

$M|A, \alpha, \mu$

Semi-Markov dynamic program

Temporal shapes update:

$\alpha|A, M$

Closed form update

Activations update:

$A|M, X, \alpha, \sigma$

Exponentiated gradient ascent

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# Learning and Inference

Note events update:

$$M|A, \alpha, \mu$$

Semi-Markov dynamic program

Temporal shapes update:

$$\alpha|A, M$$

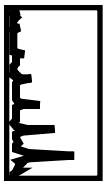
Closed form update

Activations update:

$$A|M, X, \alpha, \sigma$$

Exponentiated gradient ascent

Spectral shapes update:



$$\sigma|A, X$$

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# Learning and Inference

Note events update:

$M|A, \alpha, \mu$

Semi-Markov dynamic program

Temporal shapes update:

$\alpha|A, M$

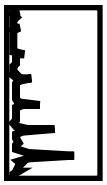
Closed form update

Activations update:

$A|M, X, \alpha, \sigma$

Exponentiated gradient ascent

Spectral shapes update:



$\sigma|A, X$

Exponentiated gradient ascent

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# Evaluation

## Onset F1

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# Evaluation

## Onset F1

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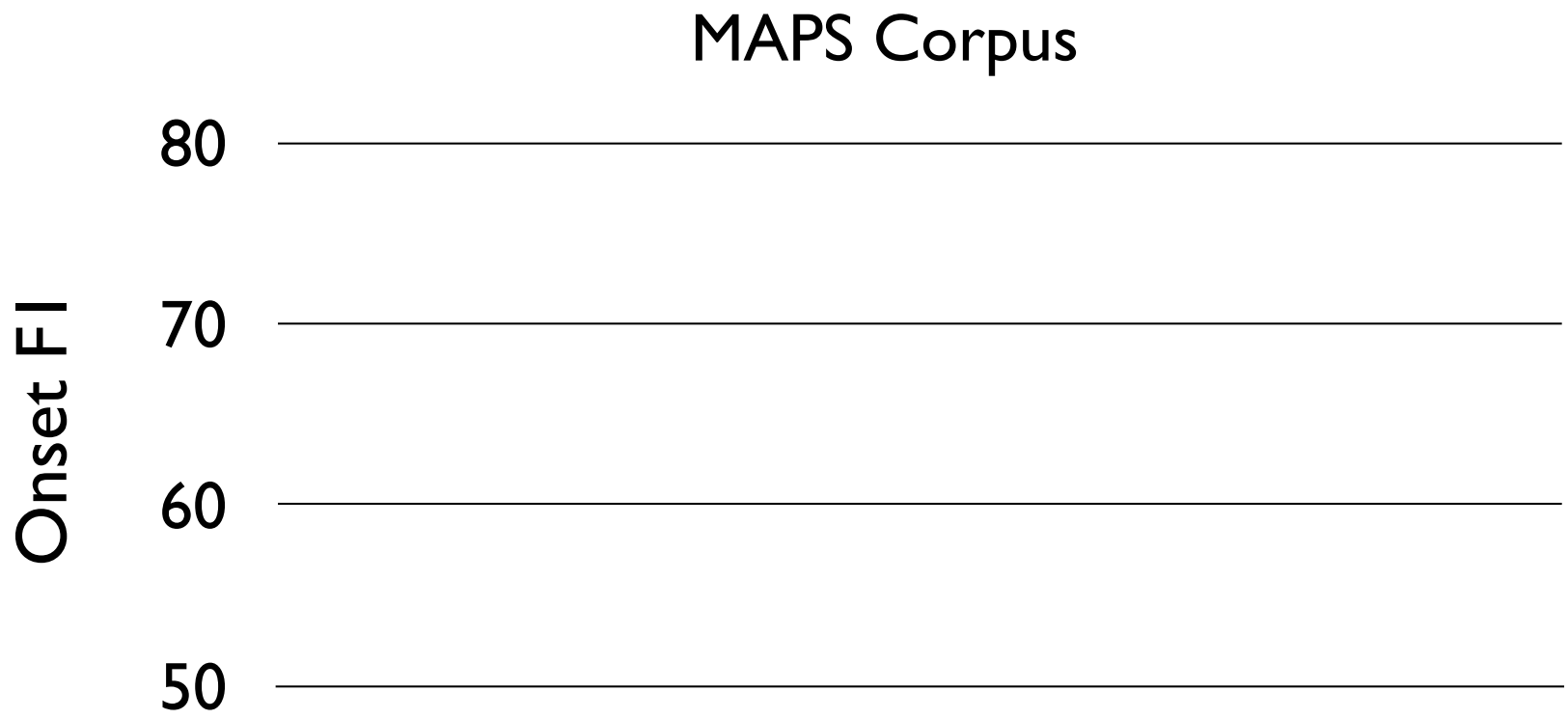
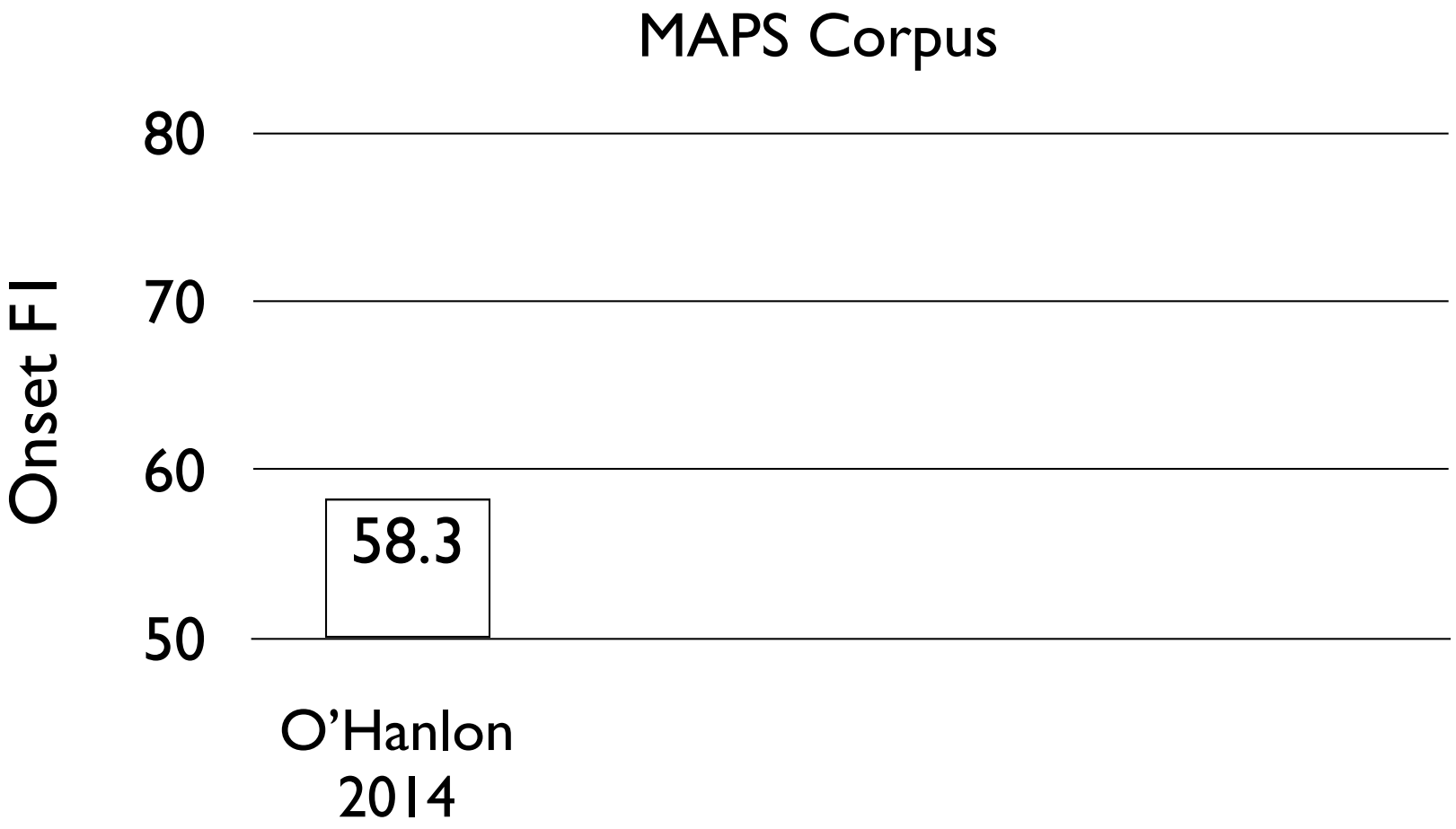
# Results



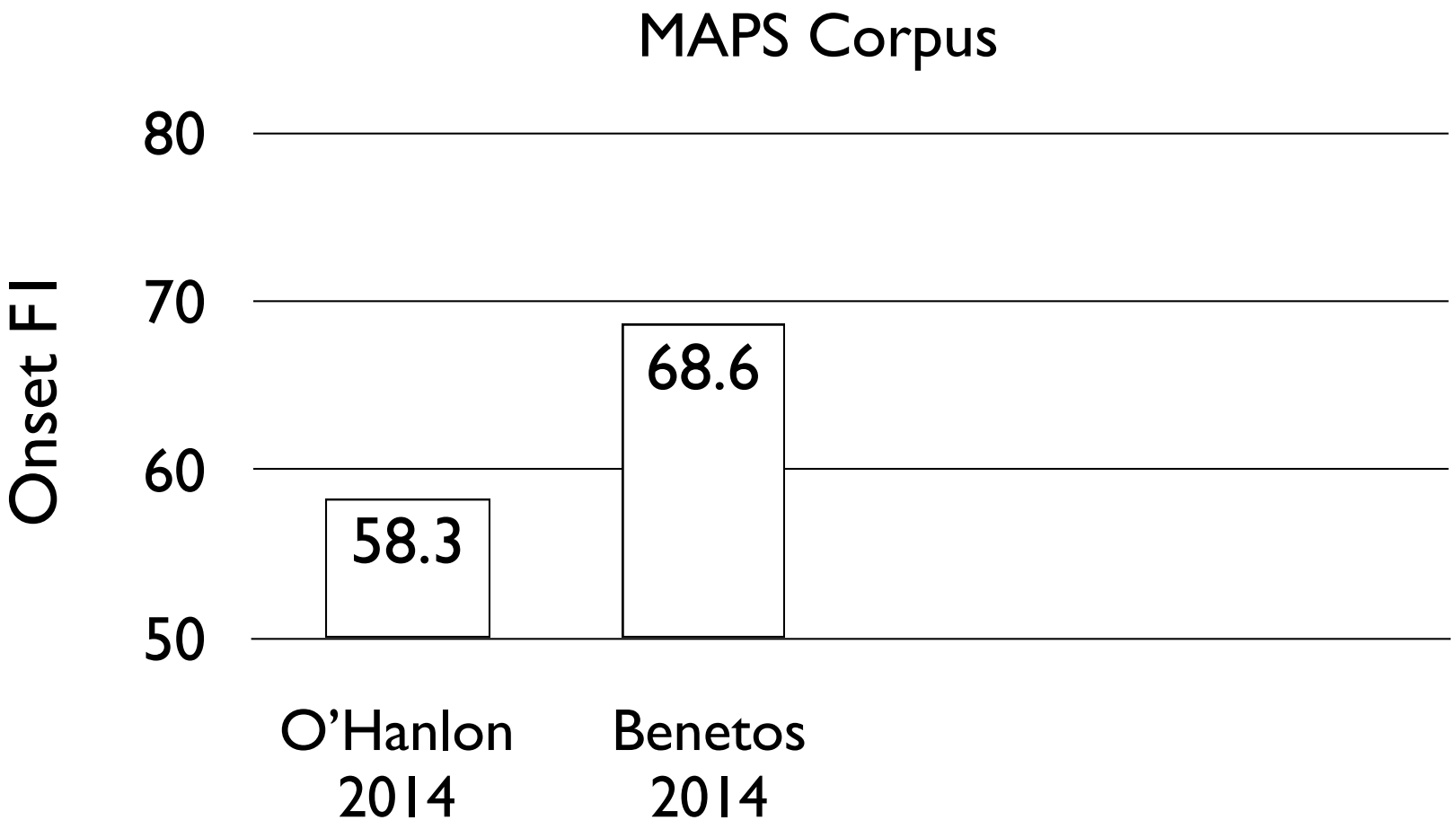

[Valentin et al. 2010]

# Results



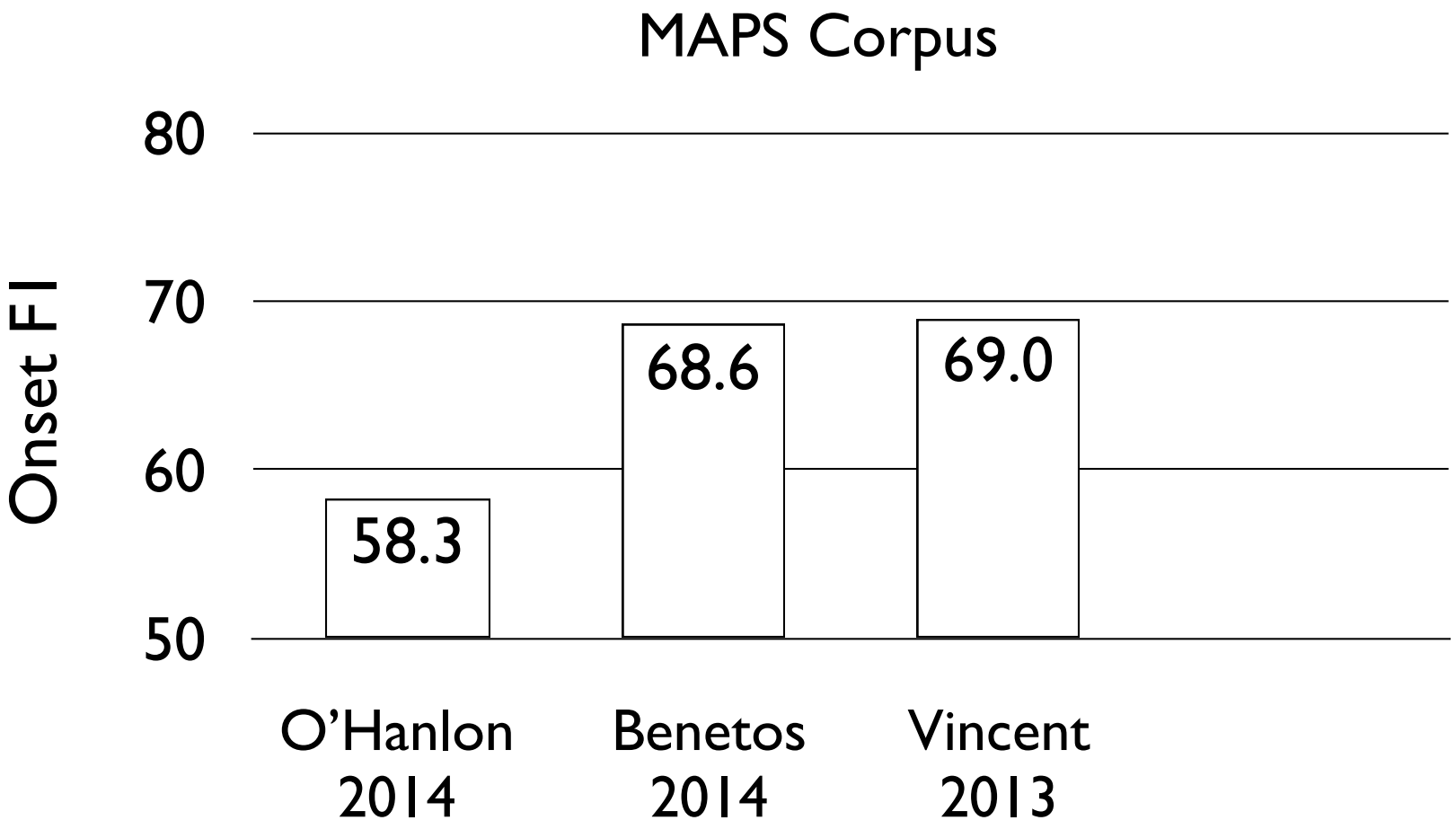

[Valentin et al. 2010]

# Results



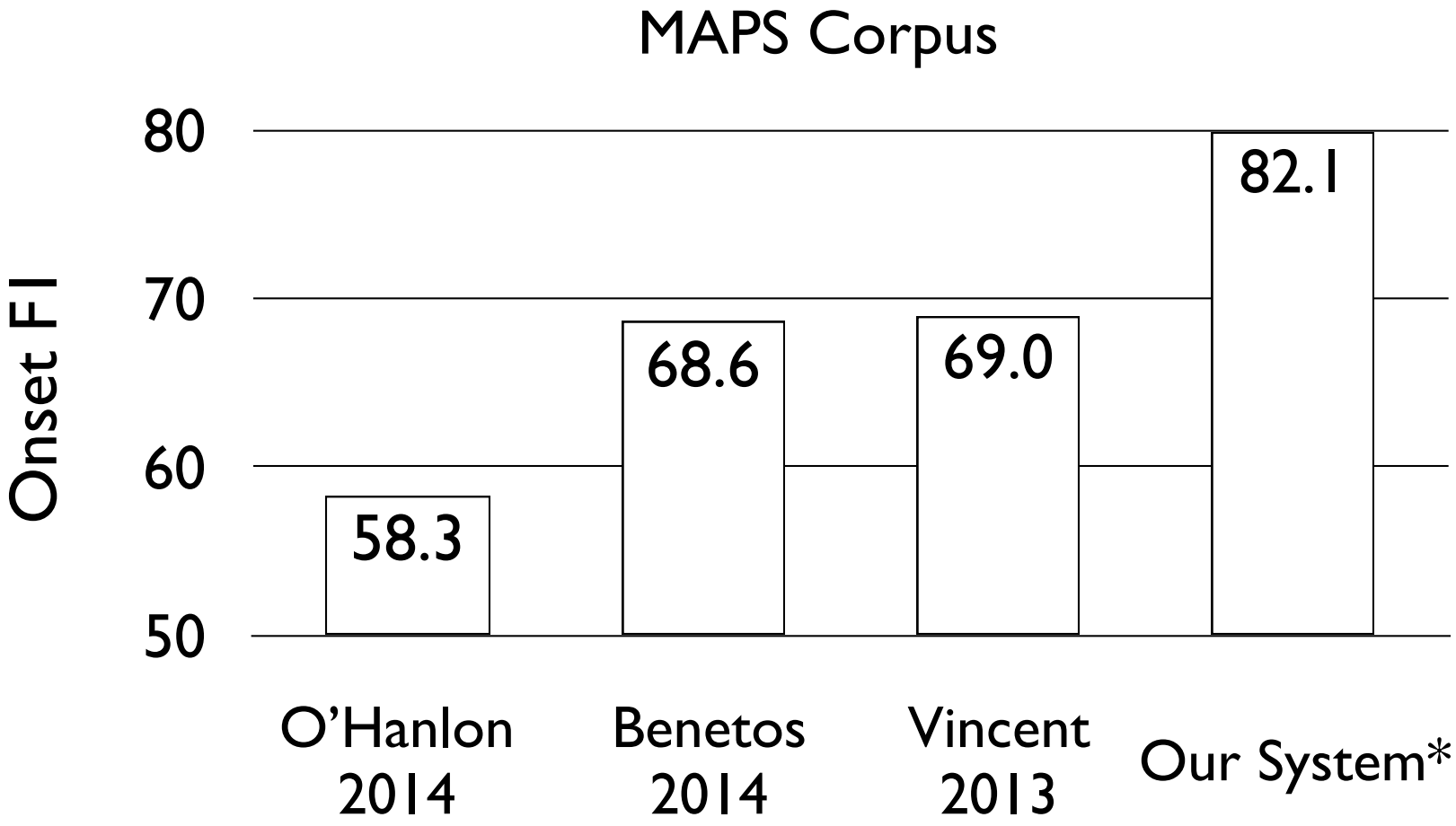

[Valentin et al. 2010]

# Results




[Valentin et al. 2010]

# Results




[Valentin et al. 2010]

[Berg-Kirkpatrick et al. 2014]


# Transcription

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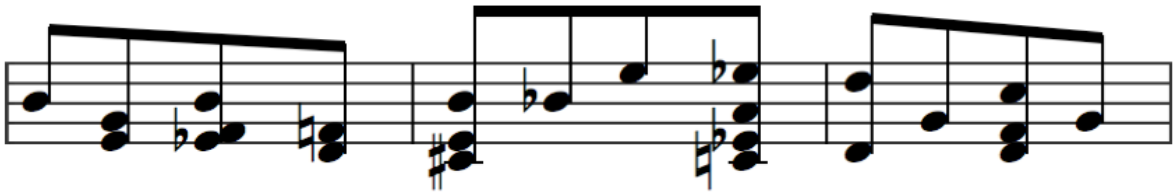
# Transcription

## Reference



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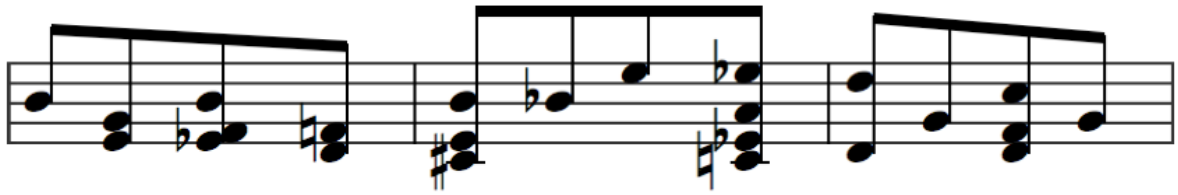
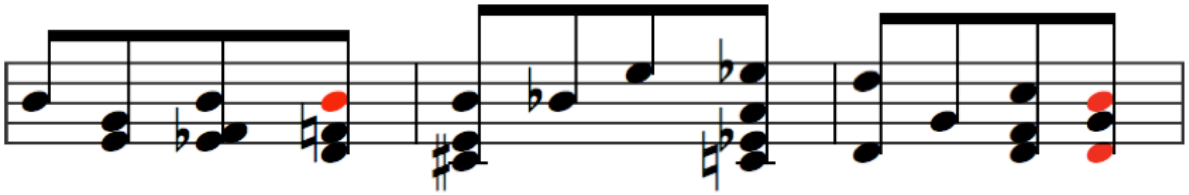
# Transcription

## Reference



## Predicted




# Resynthesized Examples


# Resynthesized Examples

Grieg input


# Resynthesized Examples

Grieg input

Grieg resynth piano


# Resynthesized Examples

Grieg input

Grieg resynth piano

Grieg resynth guitar