Automatic Summarization (and other stuff)

Berkeley NLP

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CS 288 UC Berkeley

Summarization

Summarization

Multidocument Summarization

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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Maximum Marginal Relevance

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S_9 S_2 S_5 S_1 S_4 S_7 S_3 S_8 S_6

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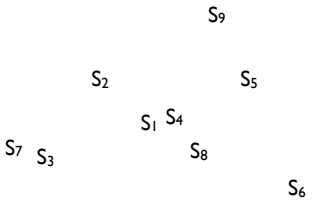

S_1: She traveled to France on Friday.
S_4: On Friday, She took a trip to France.

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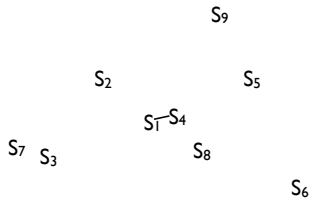

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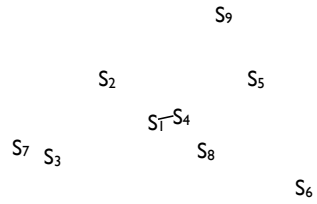

S_1: She traveled to France on Friday.
S_4: On Friday, She took a trip to France.
S_8: She plans to stay for two weeks.

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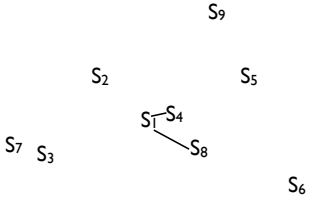

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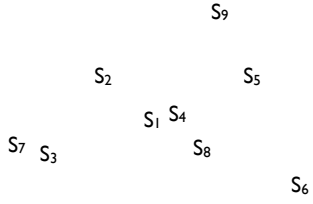

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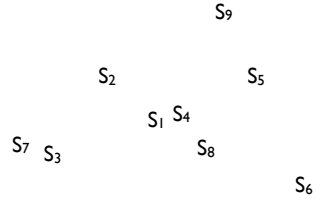

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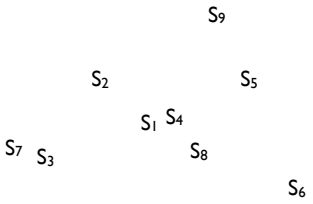

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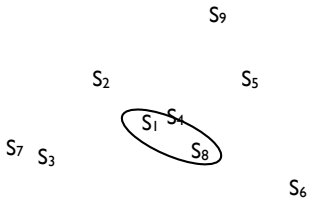

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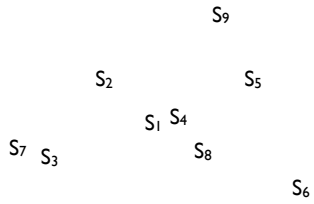

$$\underset{i \in D \setminus S}{\operatorname{argmax}} \left[\lambda \cdot \operatorname{sim}(S_i, D) - (1 - \lambda) \cdot \max_j \left(\operatorname{sim}(S_i, S_j) \right) \right]$$

[Carbonell and Goldstein, 1998]

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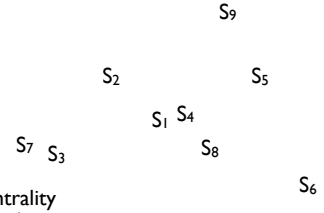

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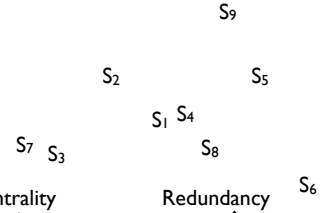

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Max Coverage

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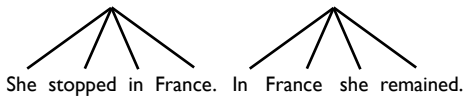

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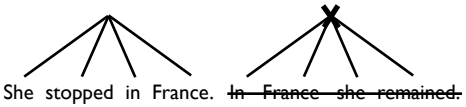

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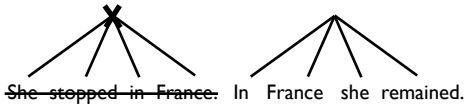
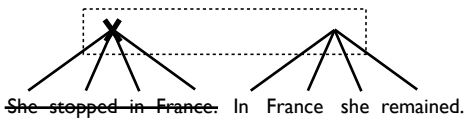


Max Coverage

A summary is a set of cuts: S



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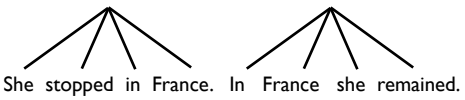

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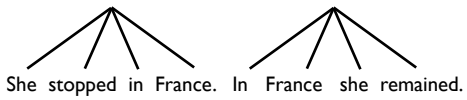

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(in, france) ✓
(france, she) ✓
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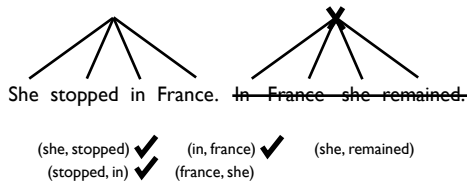

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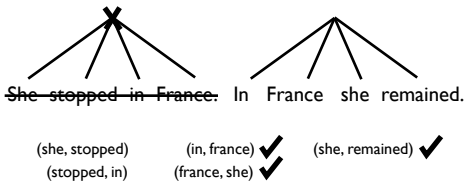

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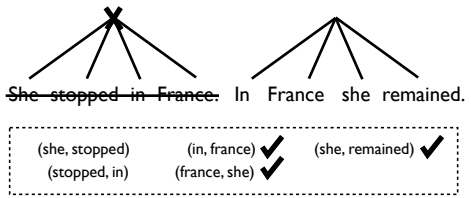

Set of bigrams covered by summary: $B(s)$

Max Coverage

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

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

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[Gillick and Favre 2008]

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

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bigrams in s are covered

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bigrams in s are covered

only bigrams in s are covered

ILP for Decoding

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

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

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

Linear Model for Extraction

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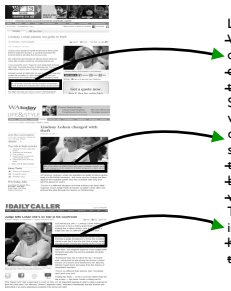

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[Martins and Smith 2009]
[Woodsend and Lapata 2010]

Extraction and Compression

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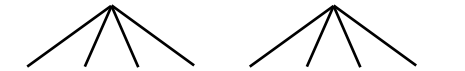
Joint Extractive / Compressive Model



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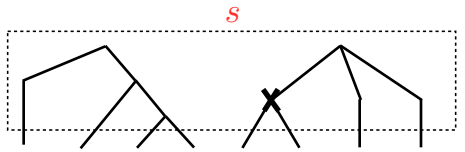
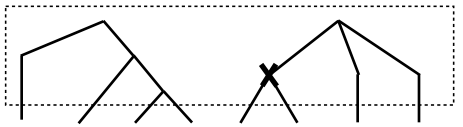


Joint Extractive / Compressive Model

s



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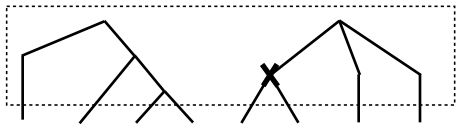

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$B(s)$

Joint Extractive / Compressive Model

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$B(s)$

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

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Parameterize using features:

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

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

Learning

Linear prediction:

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

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 $f(c)$

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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

Features

Bigram Features $f(b)$

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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

Obtaining Training Data

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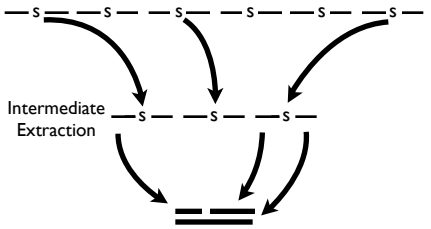
Obtaining Training Data

TAC 2009: 44 Document Collections



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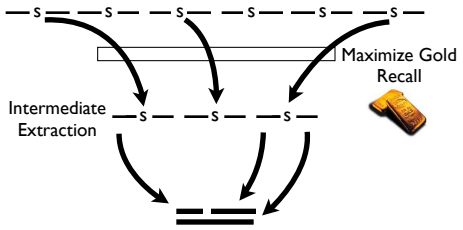

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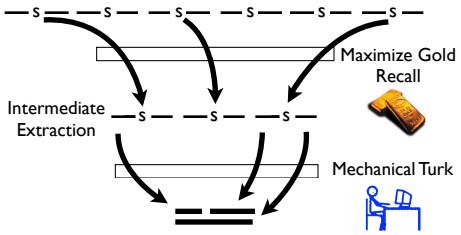

Learning

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Structured SVM Training:

Learning

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

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

score of gold exceeds score of guess by loss

Learning

Structured SVM Training:

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

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

Learning

Structured SVM Training:

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

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Learning

Structured SVM Training:

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End-to-end summarization quality

Learning

Structured SVM Training:

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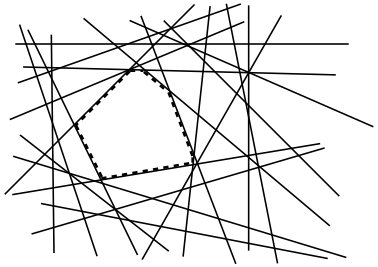
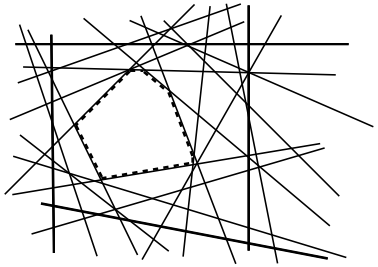
Exponentially many constraints!

Learning



[Tsochantaridis et al. 2004]

Learning



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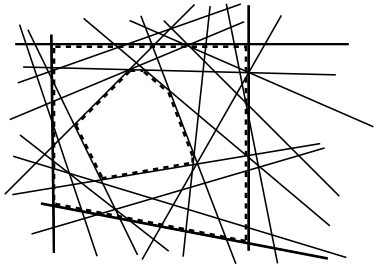
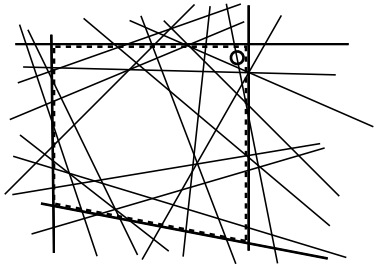


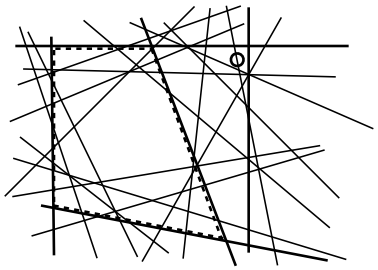
[Tsochantaridis et al. 2004]

Learning



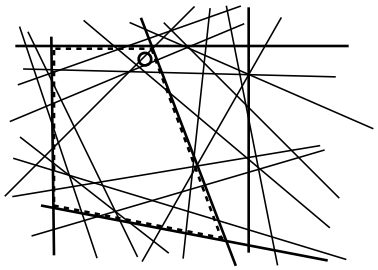
[Tsochantaridis et al. 2004]

Learning



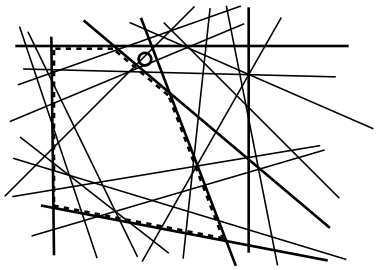
[Tsochantaridis et al. 2004]

Learning



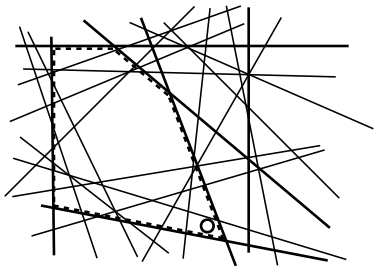
[Tsochantaridis et al. 2004]

Learning



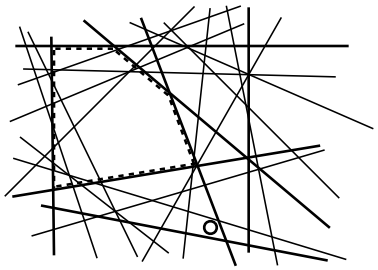
[Tsochantaridis et al. 2004]

Learning



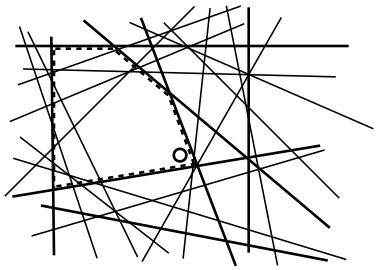
[Tsochantaridis et al. 2004]

Learning



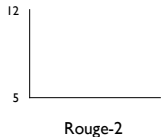
[Tsochantaridis et al. 2004]

Learning



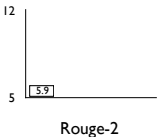
[Tsochantaridis et al. 2004]

Results



Rouge-2

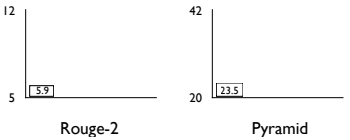
Results



Rouge-2

☐ Last Doc Baseline

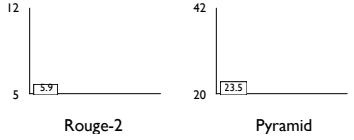
Results



Rouge-2 Pyramid

☐ Last Doc Baseline

Results



Rouge-2 Pyramid

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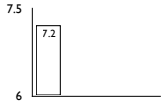
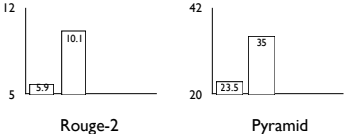


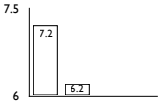
Linguistic Quality

Results



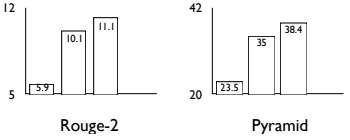
Rouge-2 Pyramid

☐ Last Doc Baseline
☐ Extractive Baseline



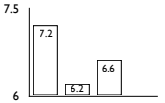
Linguistic Quality

Results



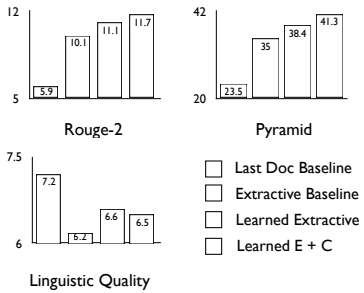
Rouge-2 Pyramid

☐ Last Doc Baseline
☐ Extractive Baseline
☐ Learned Extractive

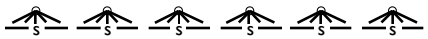


Linguistic Quality

Results



Coarse-to-fine Decoding



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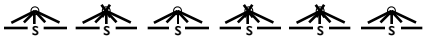

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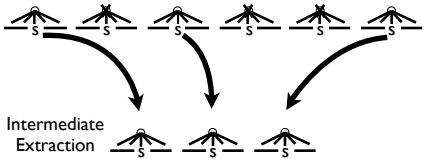

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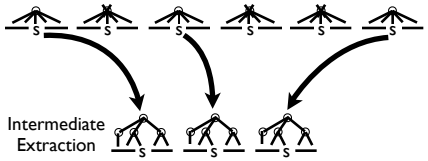

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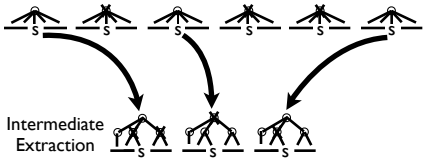

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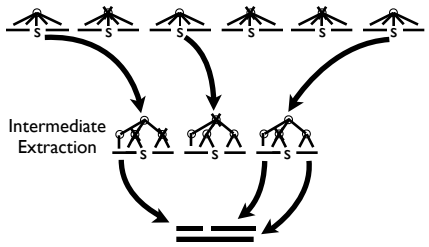

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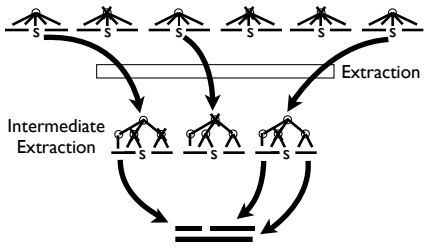

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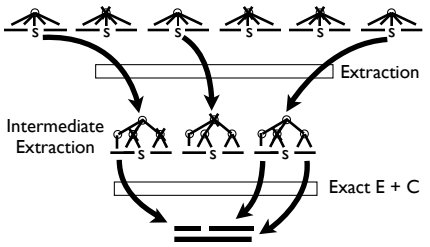

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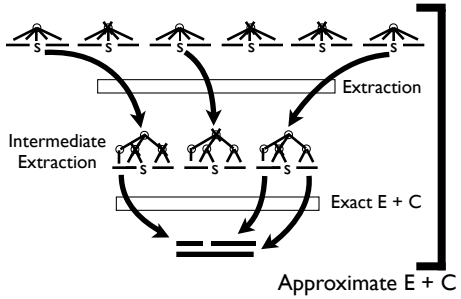

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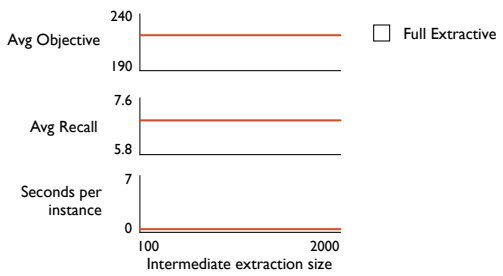

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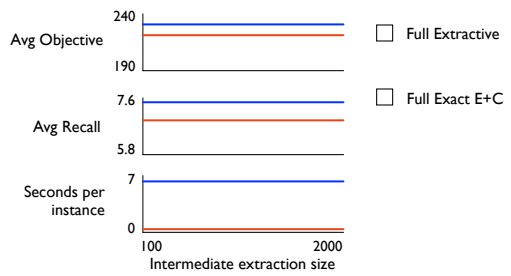

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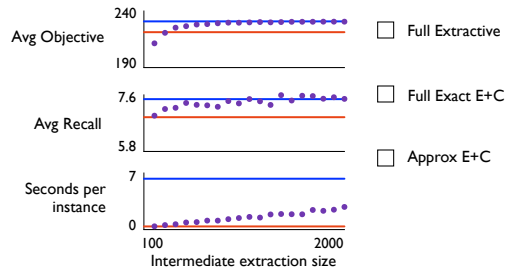

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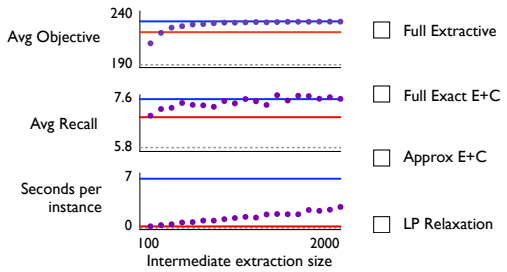

Piano Music Transcription

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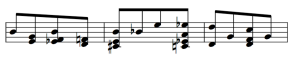

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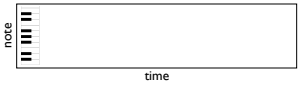
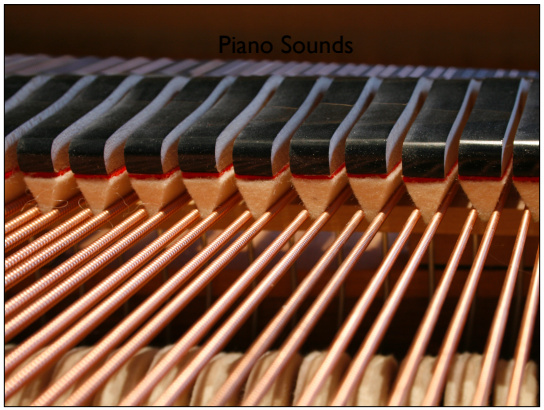
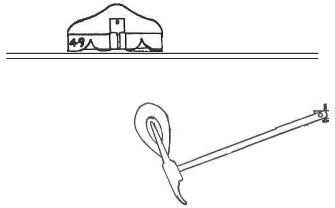
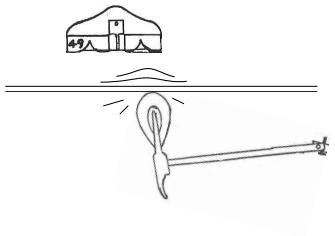




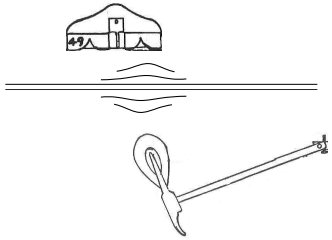
Piano Sounds



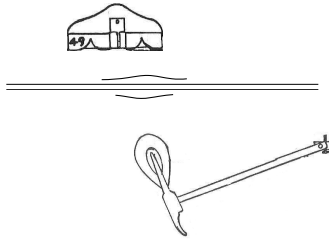
Piano Sounds



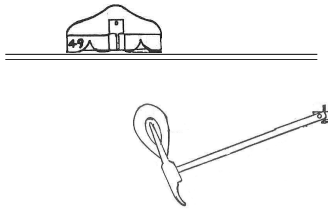
Piano Sounds



Piano Sounds



Piano Sounds



Berkeley N L P

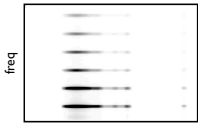
Piano Sounds

Berkeley N L P

Piano Sounds

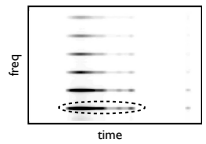
Berkeley N L P

Piano Sounds



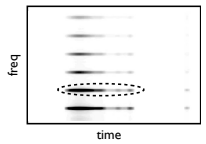
Berkeley N L P

Piano Sounds



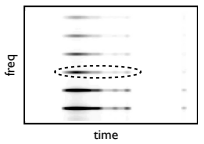
Berkeley N L P

Piano Sounds



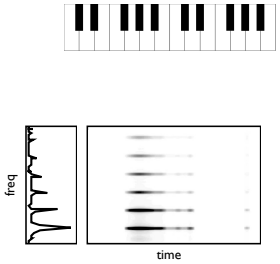
Berkeley N L P

Piano Sounds



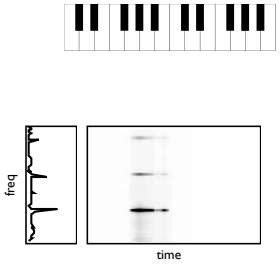
Berkeley N L P

Spectral Shape



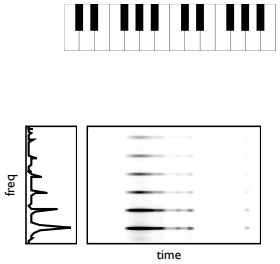
Berkeley N L P

Spectral Shape



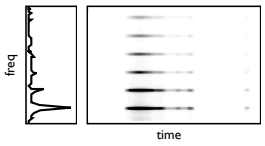
Berkeley N L P

Spectral Shape



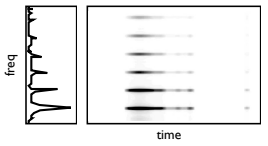
Berkeley N L P

Spectral Shape



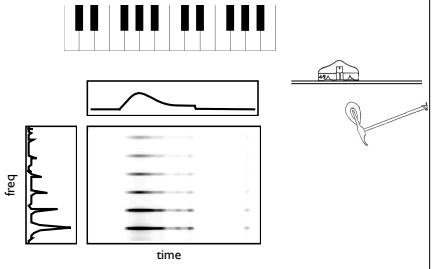
Berkeley N L P

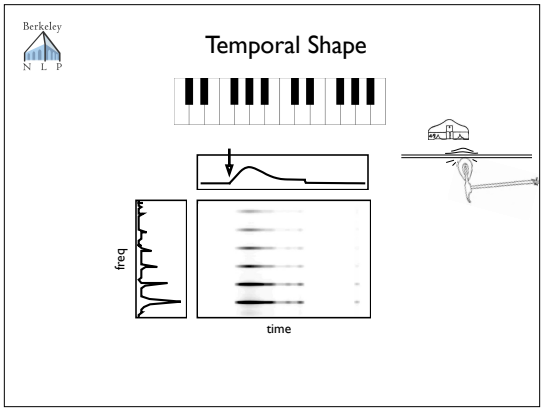
Temporal Shape

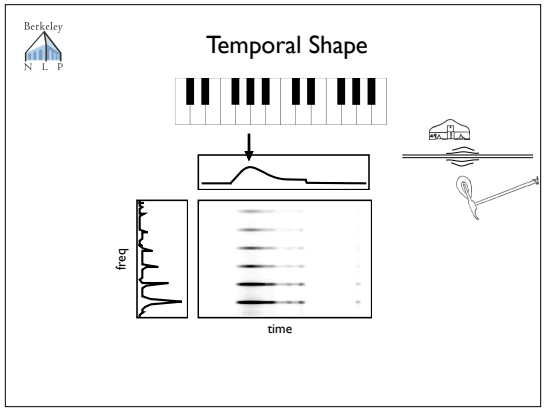


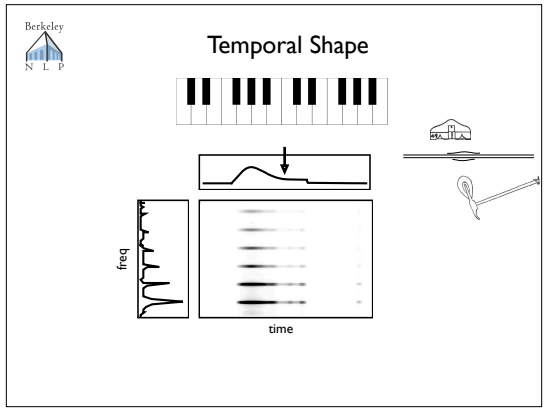
Berkeley N L P

Temporal Shape




Berkeley
N L P
Temporal Shape
freq
time


Berkeley
N L P
Temporal Shape
freq
time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Temporal Shape
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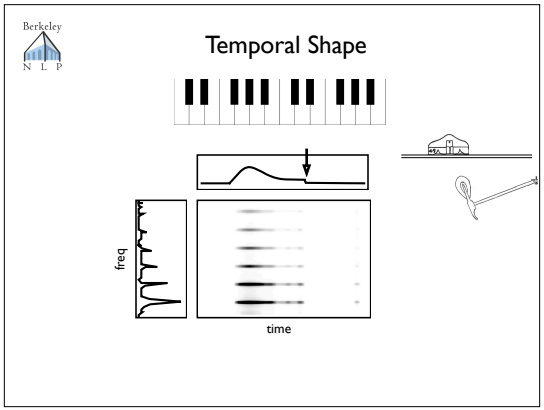
Berkeley
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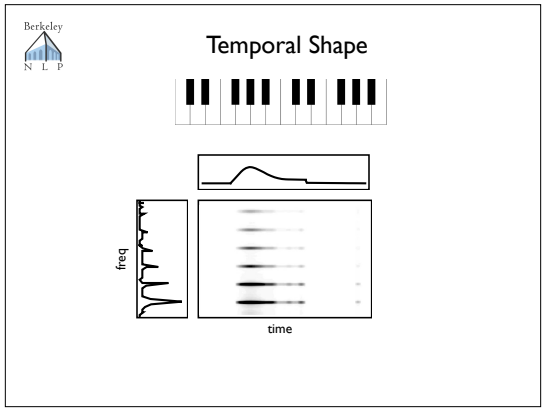
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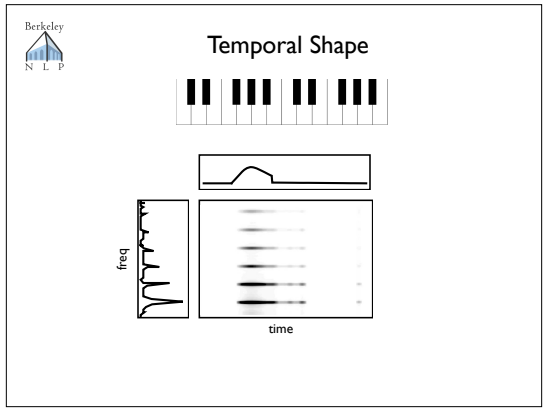
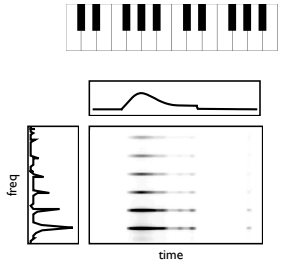
Temporal Shape
freq
time


Berkeley
N L P
Temporal Shape
freq
time

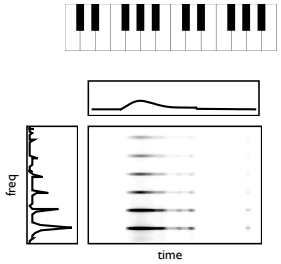
Berkeley N L P

Temporal Shape



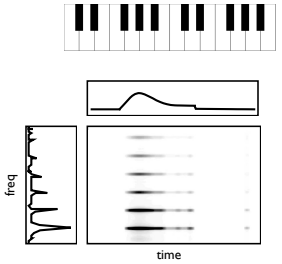
Berkeley N L P

Temporal Shape



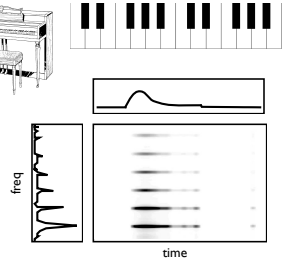
Berkeley N L P

Temporal Shape



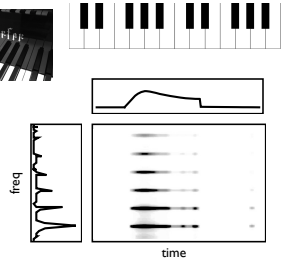
Berkeley N L P

Temporal Shape



Berkeley N L P

Temporal Shape

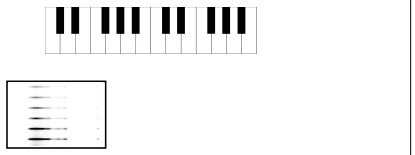


Berkeley N L P

Polyphony

Berkeley N L P

Polyphony



Berkeley N L P

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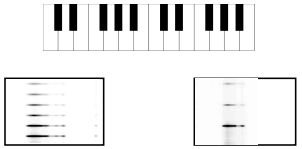
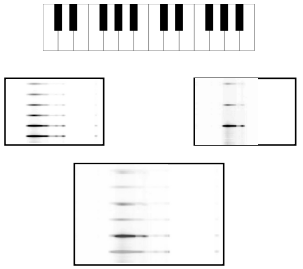


Berkeley N L P

Polyphony



Berkeley N L P

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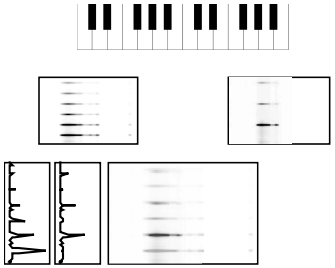

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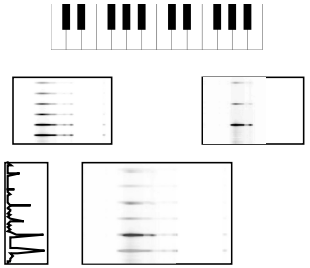

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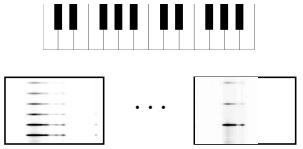

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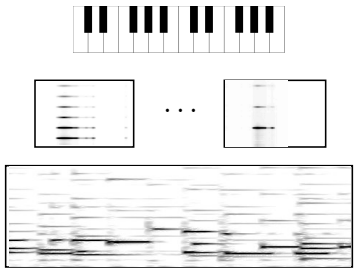
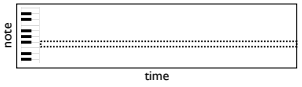


Generative Model

Generative Model



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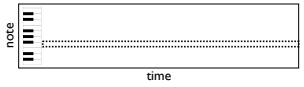

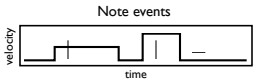

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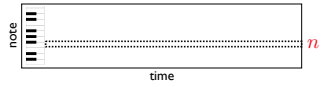

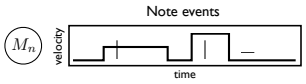

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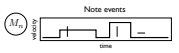

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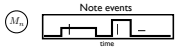
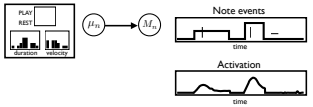


Generative Model

Generative Model



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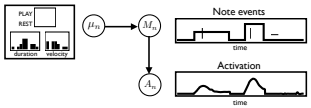

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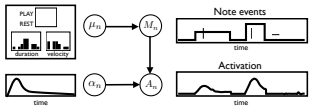

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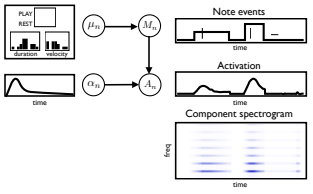
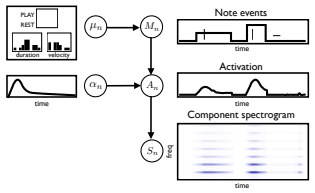


Berkeley N L P

Generative Model



Berkeley N L P

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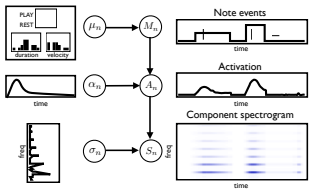

Berkeley N L P

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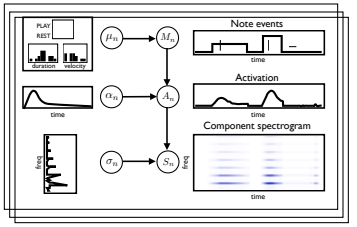

Berkeley N L P

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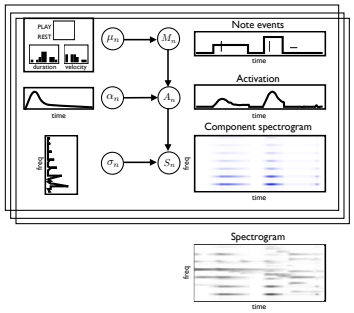

Berkeley N L P

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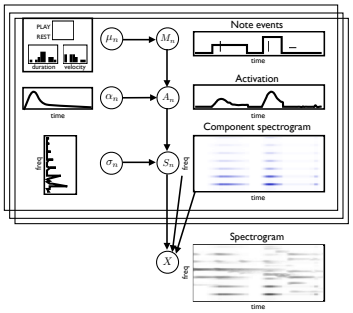
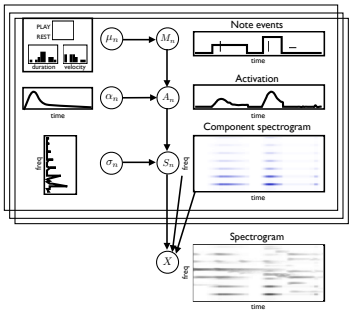


Berkeley N L P

Generative Model

Latent variables



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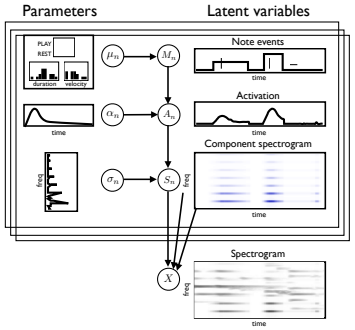
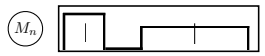


Note Event Model

Note Event Model

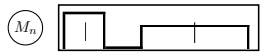


Note Event Model

Note Event Model

Event type

Note Event Model

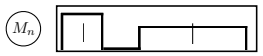


Event type

PLAY

E_1

Note Event Model



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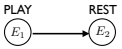

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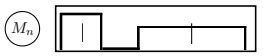
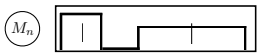


Event type

Note Event Model



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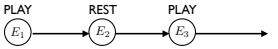

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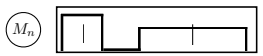

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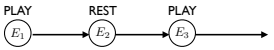

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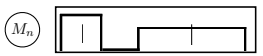
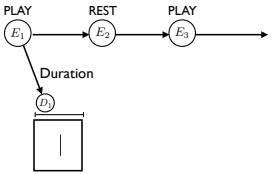
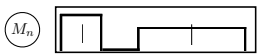


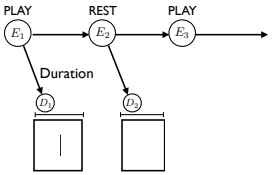
Event type

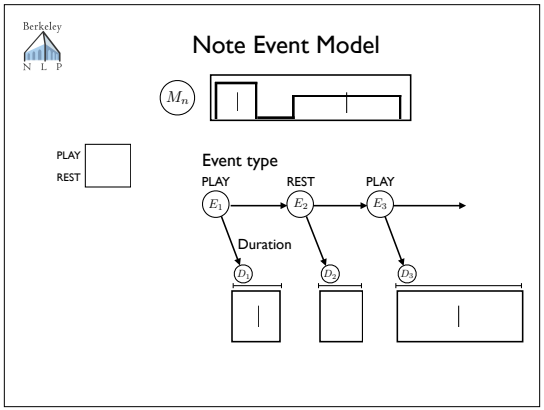


Note Event Model



Event type




Berkeley
N L P
Note Event Model
M_n
PLAY
REST
Event type
PLAY
REST
PLAY
E_1
E_2
E_3
Duration
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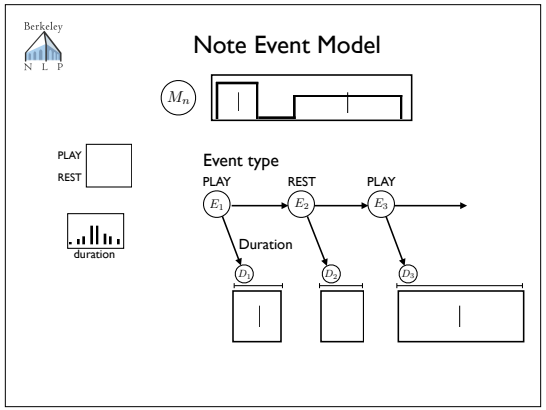
D_2
D_3


Berkeley
N L P
Note Event Model
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duration
Event type
PLAY
REST
PLAY
E_1
E_2
E_3
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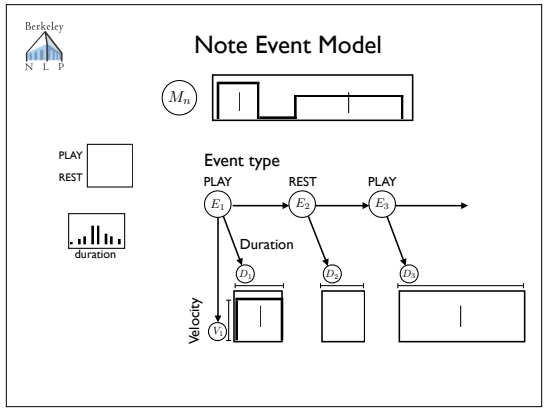
D_2
D_3


Berkeley
N L P
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M_n
PLAY
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duration
Event type
PLAY
REST
PLAY
E_1
E_2
E_3
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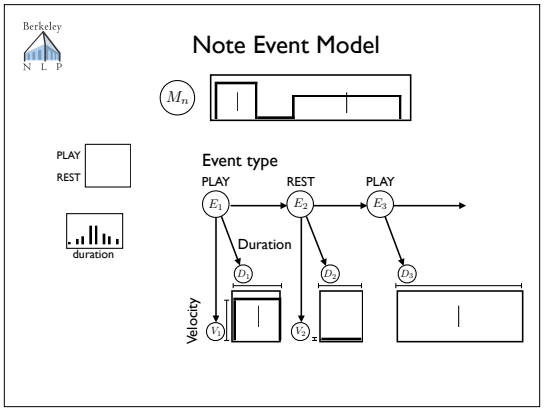
Velocity
V_1


Berkeley
N L P
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REST
duration
Event type
PLAY
REST
PLAY
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E_3
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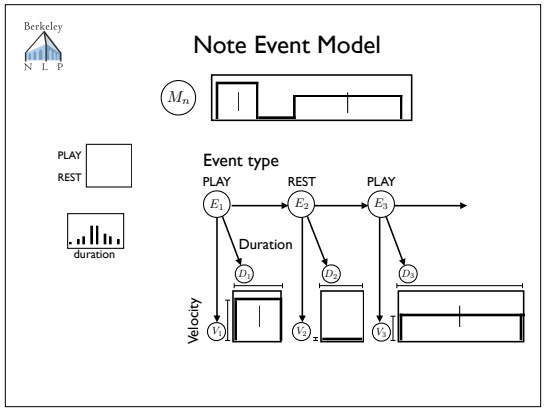
V_1
V_2


Berkeley
N L P
Note Event Model
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PLAY
REST
duration
Event type
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D_1
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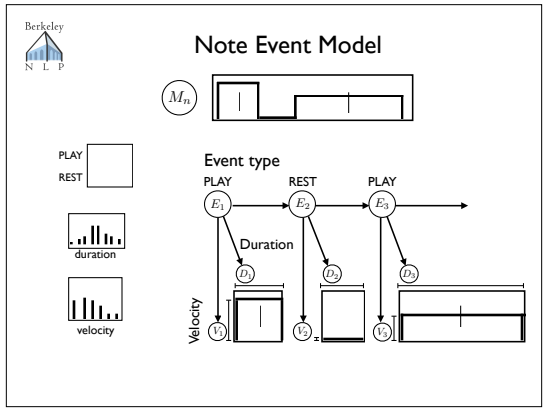
V_1
V_2
V_3


Berkeley
N L P
Note Event Model
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REST
duration
velocity
Event type
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Duration
D_1
D_2
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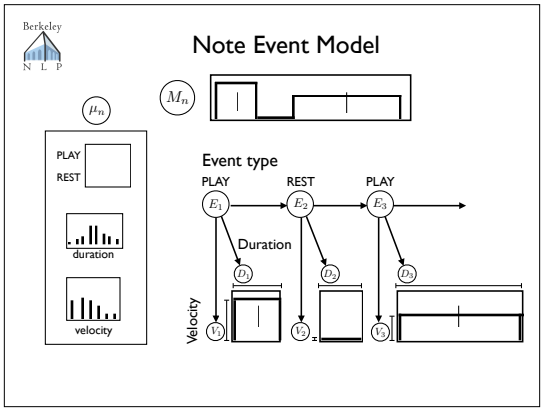
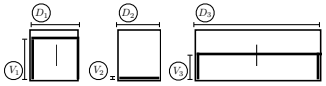
Velocity
V_1
V_2
V_3

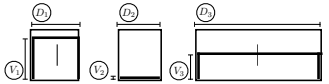
Note Event Model



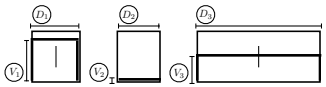
Activation Model



Activation Model



Activation Model



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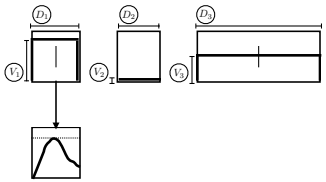
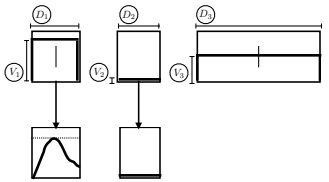
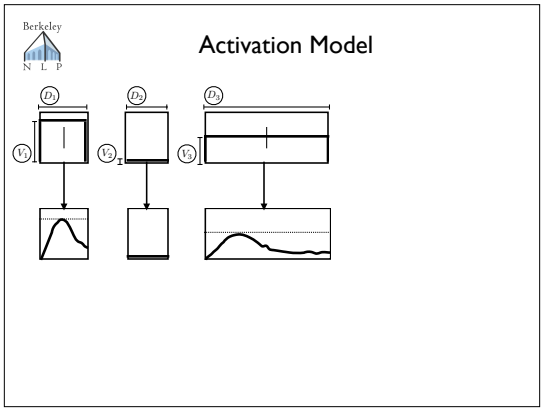
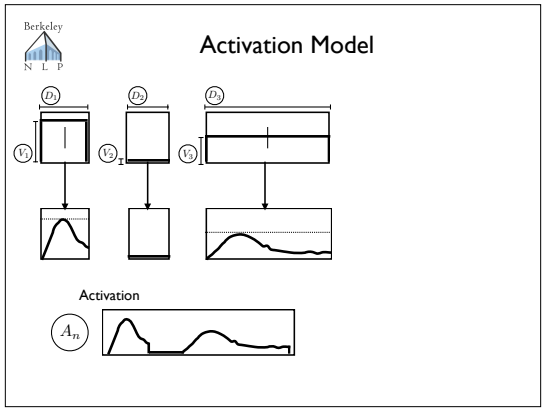


Activation Model




Berkeley
N L P
Activation Model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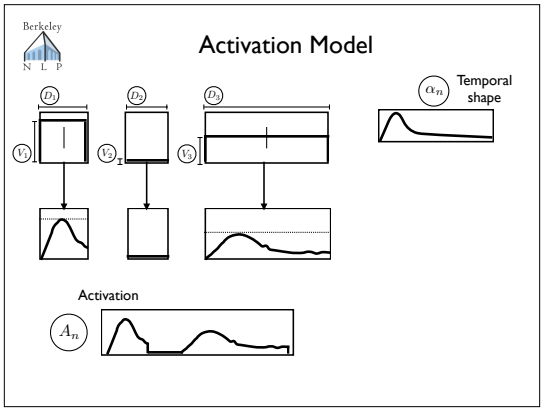
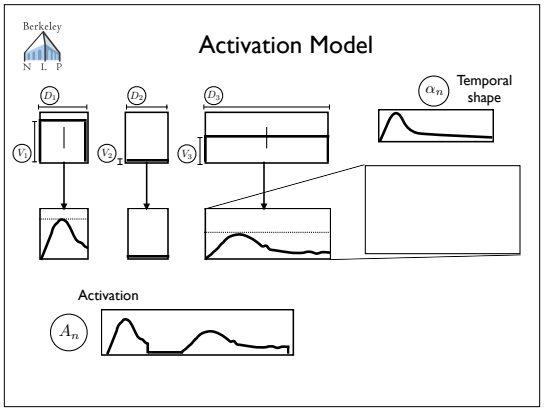
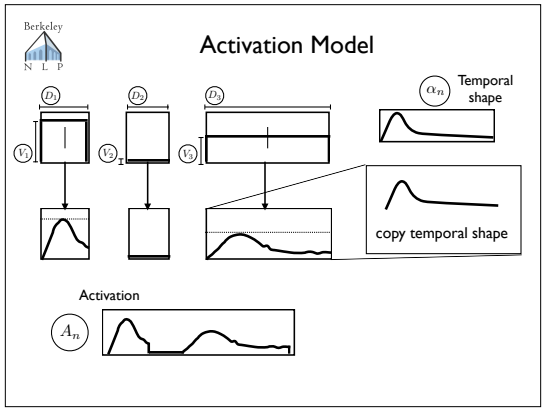
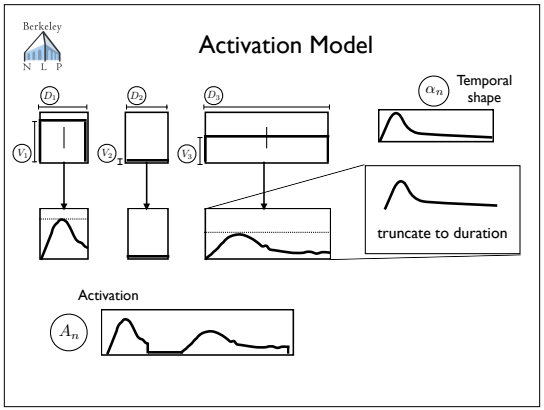
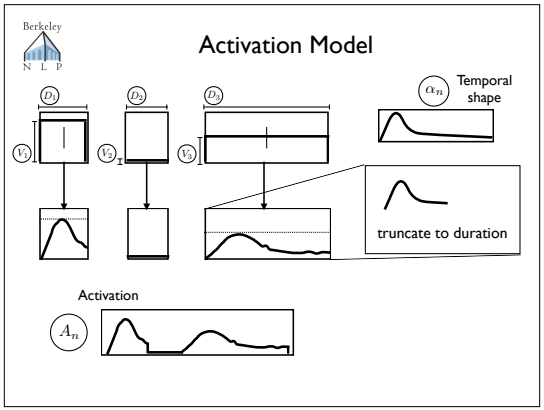
N L P
Activation Model
Activation

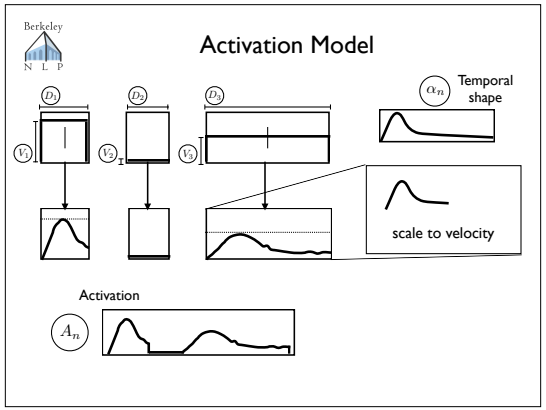

Berkeley
N L P
Activation Model
Temporal shape
Activation

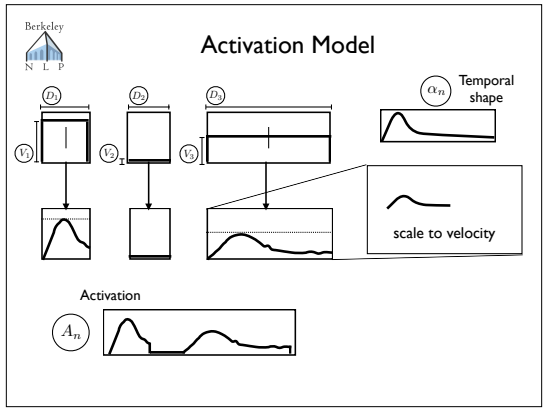

Berkeley
N L P
Activation Model
Temporal shape
Activation

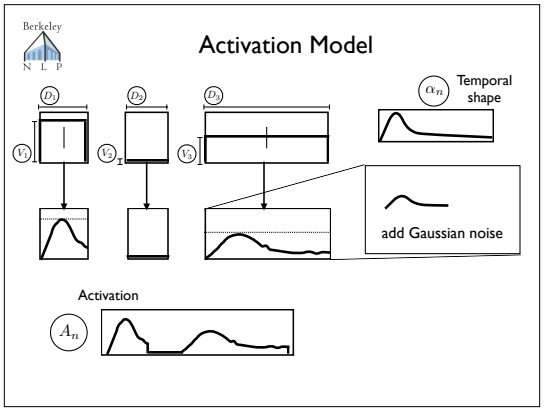

Berkeley
N L P
Activation Model
Temporal shape
copy temporal shape
Activation

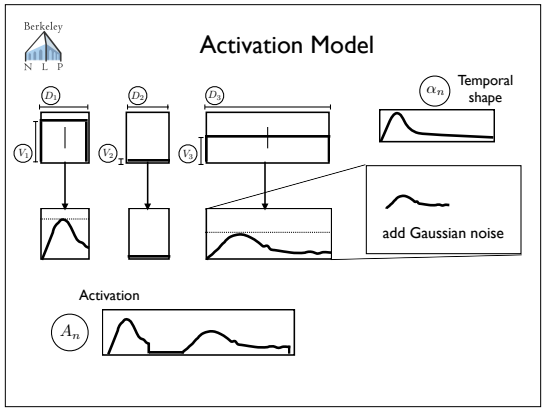

Berkeley
N L P
Activation Model
Temporal shape
truncate to duration
Activation

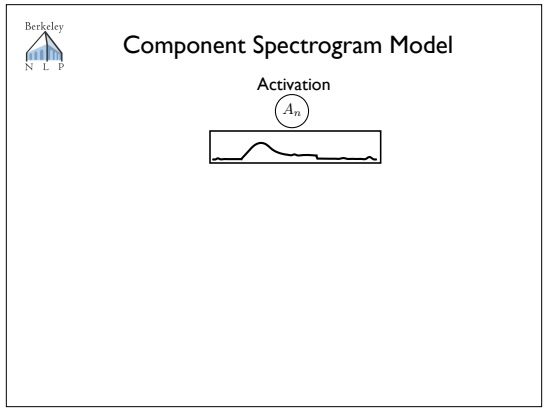

Berkeley
N L P
Activation Model
D_1
D_2
D_3
α_n
Temporal shape
V_1
V_2
V_3
truncate to duration
Activation
A_n


Berkeley
N L P
Activation Model
D_1
D_2
D_3
α_n
Temporal shape
V_1
V_2
V_3
scale to velocity
Activation
A_n

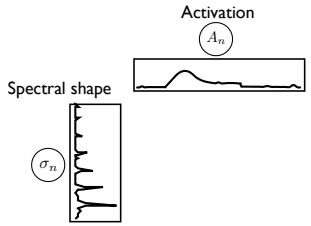

Berkeley
N L P
Activation Model
D_1
D_2
D_3
α_n
Temporal shape
V_1
V_2
V_3
scale to velocity
Activation
A_n


Berkeley
N L P
Activation Model
D_1
D_2
D_3
α_n
Temporal shape
V_1
V_2
V_3
add Gaussian noise
Activation
A_n

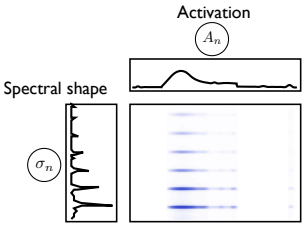

Berkeley
N L P
Activation Model
D_1
D_2
D_3
α_n
Temporal shape
V_1
V_2
V_3
add Gaussian noise
Activation
A_n


Berkeley
N L P
Component Spectrogram Model
Activation
A_n

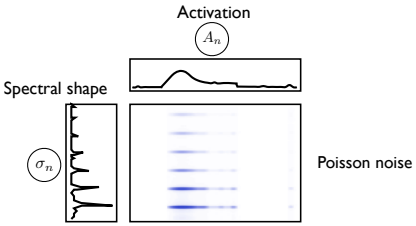
Component Spectrogram Model



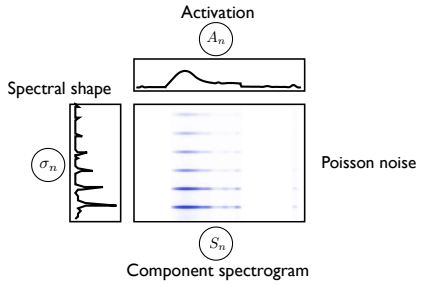
Component Spectrogram Model



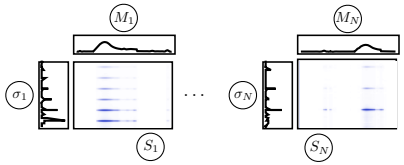
Component Spectrogram Model



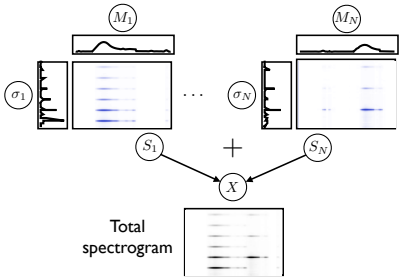
Component Spectrogram Model



Total Spectrogram Model

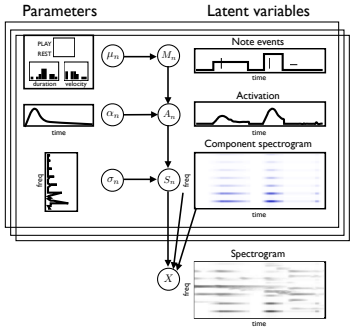


Total Spectrogram Model



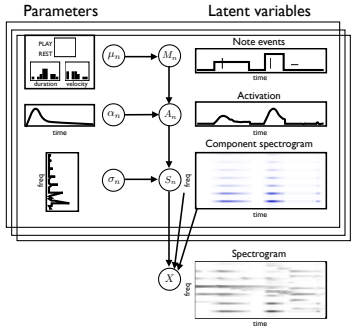
Berkeley N L P

Learning and Inference



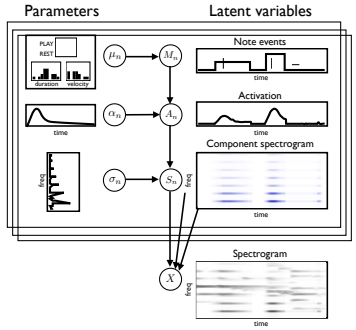
Berkeley N L P

Learning and Inference



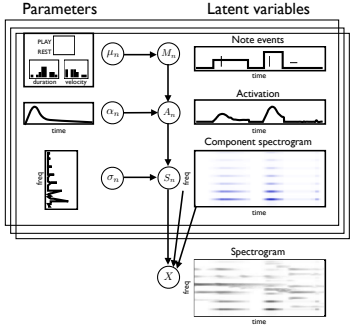
Berkeley N L P

Learning and Inference



Berkeley N L P

Learning and Inference



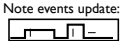
Berkeley N L P

Learning and Inference

Berkeley N L P

Learning and Inference

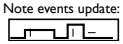
Note events update:



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

Learning and Inference

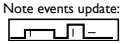
Note events update:



$M|A, \alpha, \mu$ Semi-Markov dynamic program

Learning and Inference

Note events update:



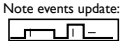
$M|A, \alpha, \mu$ Semi-Markov dynamic program

Temporal shapes update:

$\alpha|A, M$

Learning and Inference

Note events update:



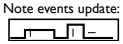
$M|A, \alpha, \mu$ Semi-Markov dynamic program

Temporal shapes update:

$\alpha|A, M$ Closed form update

Learning and Inference

Note events update:

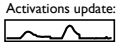


$M|A, \alpha, \mu$ Semi-Markov dynamic program

Temporal shapes update:

$\alpha|A, M$ Closed form update

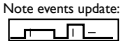
Activations update:



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

Learning and Inference

Note events update:

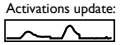


$M|A, \alpha, \mu$ Semi-Markov dynamic program

Temporal shapes update:

$\alpha|A, M$ Closed form update

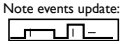
Activations update:



$A|M, X, \alpha, \sigma$ Exponentiated gradient ascent

Learning and Inference

Note events update:

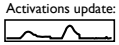


$M|A, \alpha, \mu$ Semi-Markov dynamic program

Temporal shapes update:

$\alpha|A, M$ Closed form update

Activations update:



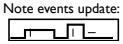
$A|M, X, \alpha, \sigma$ Exponentiated gradient ascent

Spectral shapes update:

$\sigma|A, X$

Learning and Inference

Note events update:

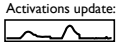


$M|A, \alpha, \mu$ — Semi-Markov dynamic program

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

Evaluation

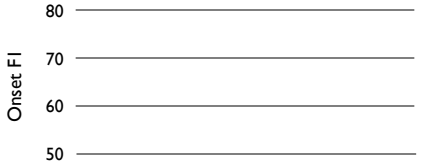
Onset F1

Evaluation

Onset F1

Results

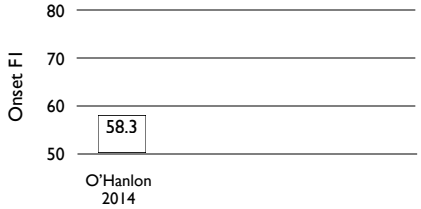
MAPS Corpus



[Valentin et al. 2010]

Results

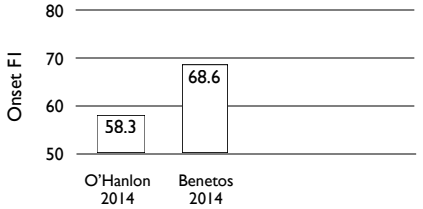
MAPS Corpus



[Valentin et al. 2010]

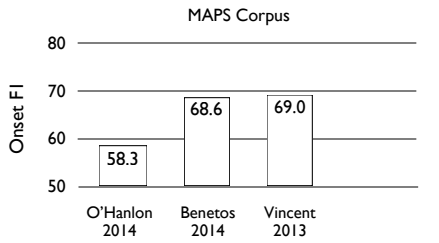
Results

MAPS Corpus



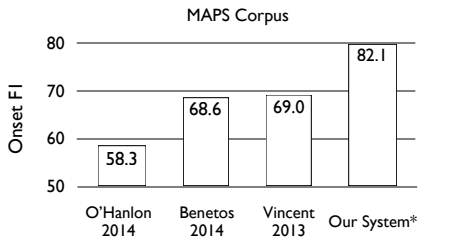
[Valentin et al. 2010]

Results



[Valentin et al. 2010]

Results

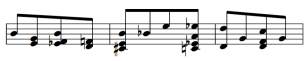


[Valentin et al. 2010]
[Berg-Kirkpatrick et al. 2014]

Transcription

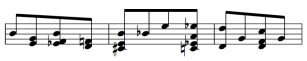
Transcription

Reference

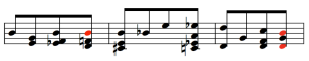


Transcription

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