# Unsupervised Pattern Learning from Sequential Experiences

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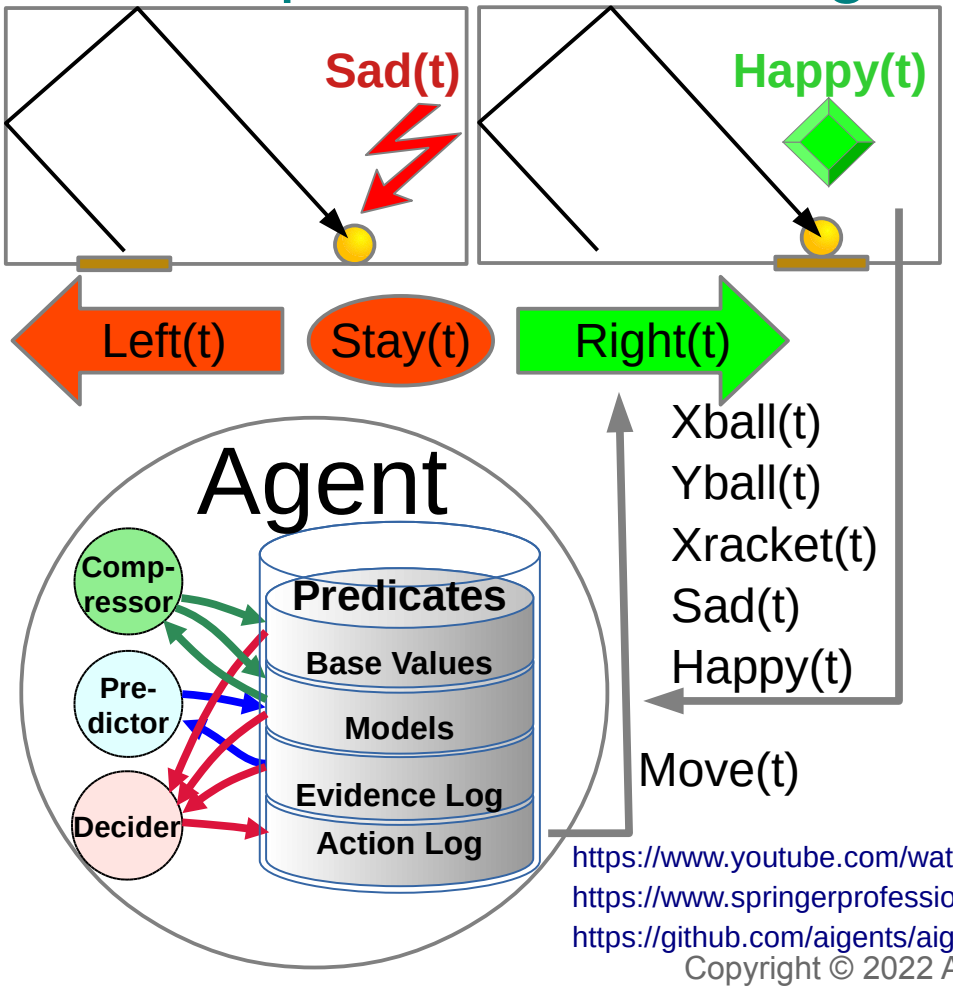
SingularityNET

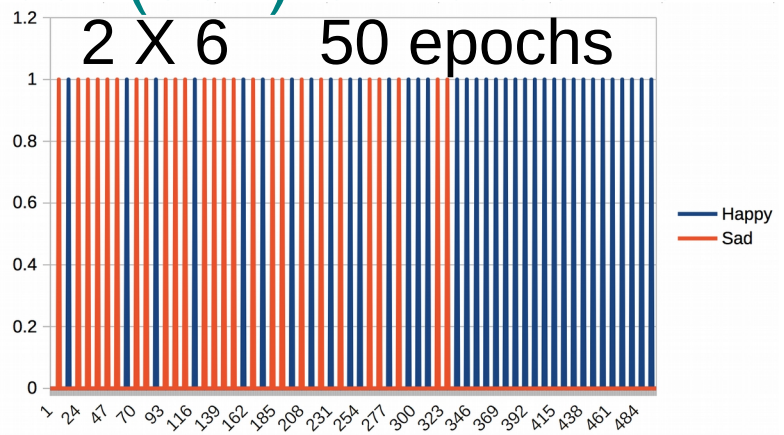
# Motivation

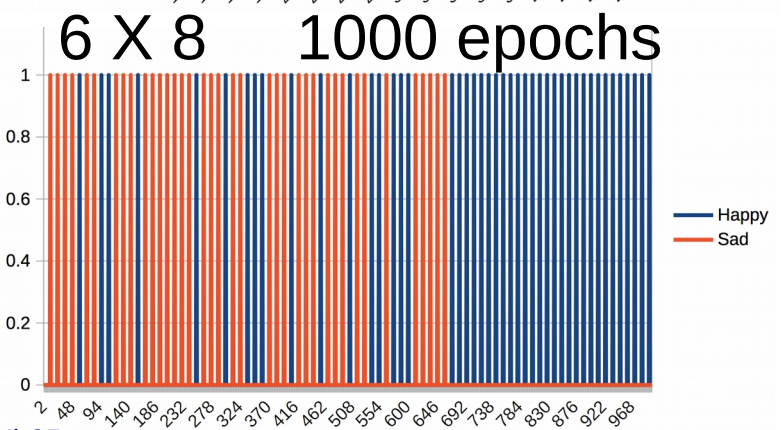
Identifying successful/unsuccessful sequential experiences for experiential learning for global (self)reinforcement

Discovering NLP patterns such as words and punctuation for further unsupervised language learning

# Identifying successful/unsuccessful sequential experiences for experiential learning with global (self)reinforcement



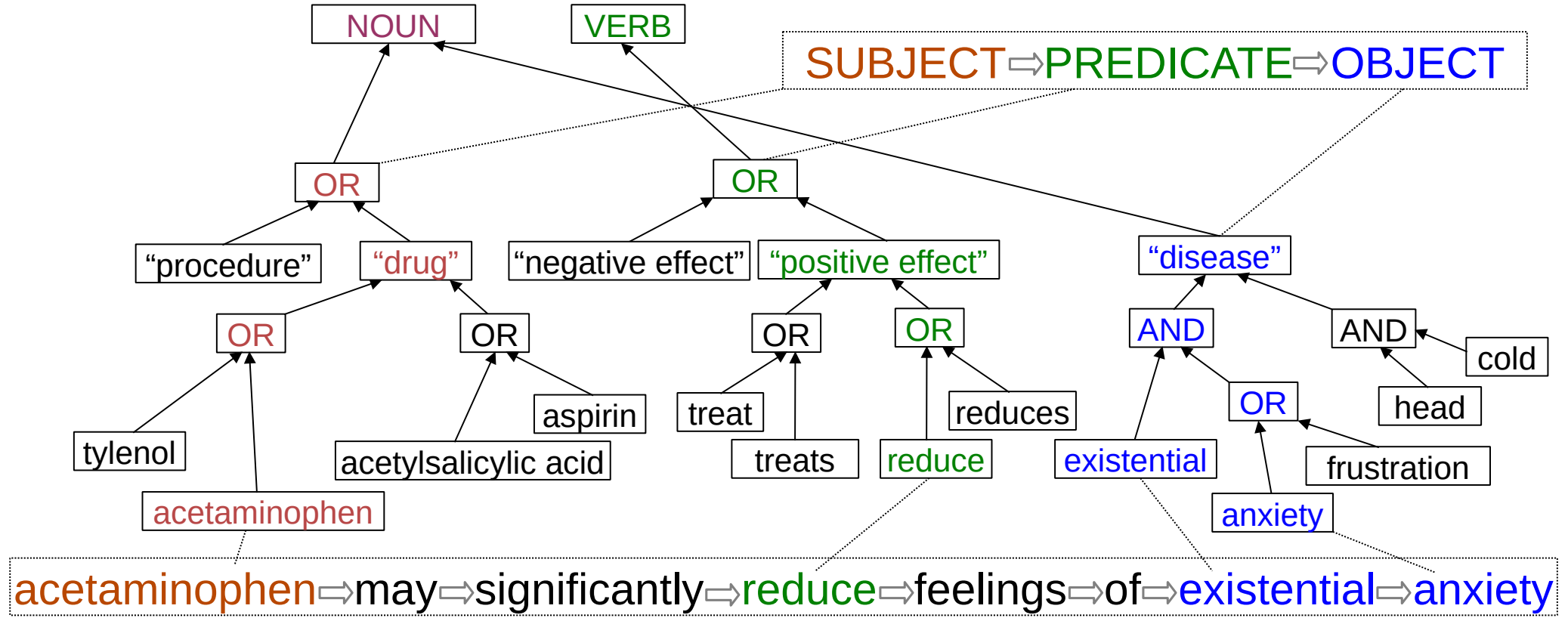




https://www.youtube.com/watch?v=2LPLhJKh95g

https://www.springerprofessional.de/neuro-symbolic-architecture-for-experiential-learning-in-discret/20008336

https://github.com/aigents/aigents-java/tree/master/src/main/java/net/webstructor/agi

# Discovering NLP patterns such as words or phrase structures for unsupervised language learning




https://ieeexplore.ieee.org/document/7361868
https://github.com/aigents/aigents-java

https://www.springerprofessional.de/unsupervised-language-learning-in-opencog/15995030
https://www.springerprofessional.de/en/programmatic-link-grammar-induction-for-unsupervised-language-le/17020348
https://github.com/singnet/language-learning/

# Issues to Address

Absence of explicit start/stop tags in continuous streams of spaces in experiential (reinforcement/self-reinforcement) learning with delayed/sparse feedback

https://www.youtube.com/watch?v=2LPLhJKh95g
https://www.springerprofessional.de/neuro-symbolic-architecture-for-experiential-learning-in-discret/20008336
https://github.com/aigents/aigents-java/tree/master/src/main/java/net/webstructor/agi

Complex, cumbersome, unreliable and expensive language-specific tokenization process for unsupervised language learning in NLP

Low quality of unsupervised parsing and tokenization learning based on mutual information and conditional probabilities

https://www.springerprofessional.de/unsupervised-language-learning-in-opencog/15995030
https://www.springerprofessional.de/en/programmatic-link-grammar-induction-for-unsupervised-language-le/17020348
https://github.com/singnet/language-learning/
https://scholarsarchive.byu.edu/cgi/viewcontent.cgi?article=6983&context=etd

# Tokenization or Text Segmentation as Language Modeling

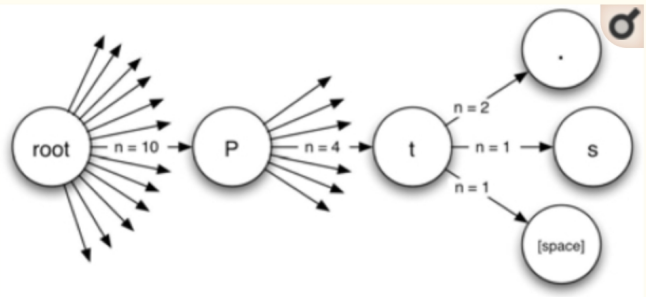



Figure 1

Trie data structure. The probability of observing an 's' given the preceding string "Pt" is ¼, or 25%. The freedom following "pt" is 3.

https://scholarsarchive.byu.edu/cgi/viewcontent.cgi?article=6983&context=etd

https://www.ncbi.nlm.nih.gov/pmc/articles/PMC2655800/

**Metrics/Indicators:**

Mutual Information

Conditional Probability

Transition Freedom

https://github.com/aigents/pygents

## Contrastive Evaluation: Test Specific Phenomena

To test if your LM knows something very specific, you can use contrastive examples. These are the examples where you have several versions of the same text which differ only in the aspect you care about: one correct and at least one incorrect. A model has to assign higher scores (probabilities) to the correct version.

The roses in the vase by the door ___ Competing answers: is, are

P(The roses in the vase by the door are)

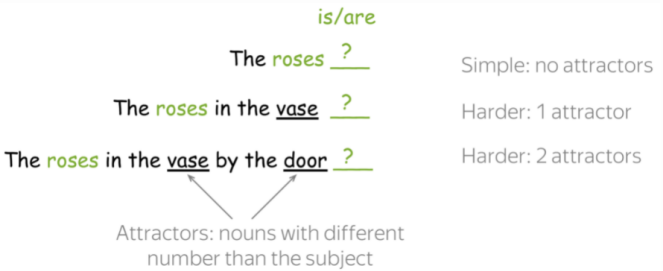
P(The roses in the vase by the door is)

Is the correct answer ranked higher?

P(...are) > P(...is)?

A very popular phenomenon to look at is subject-verb agreement, initially proposed in the Assessing the Ability of LSTMs to Learn Syntax-Sensitive Dependencies paper. In this task, contrastive examples consist of two sentences: one where the verb agrees in number with the subject, and another with the same verb, but incorrect inflection.

Examples can be of different complexity depending on the number of **attractors**: other nouns in a sentence that have different grammatical number and can "distract" a model from the subject.




https://lena-voita.github.io/nlp_course/language_modeling.html

# Claims

**Transition Freedom (TF)** appears to be superior (over **Mutual Information** and **Conditional Probability**) for unsupervised text segmentation (tokenization).

English and Russian require one specific way (variance) of handling the TF while Chinese requires a bit different specific way (derivative-based “peak values”) for the same purpose.

Tokenization quality for Russian and English may be as high as F1=0.96-1.0, depending on training and testing corpora while for Chinese the minimum is F1=0.71-0.92, depending on the assessment assumptions.

Larger training corpora does not necessarily effect in better tokenization quality, while compacting the models eliminating statistically weak evidence typically improve the quality.

TF-based tokenization appear quality same or better than lexicon-based one for Russian and English while for Chinese appears the opposite (as it could be anticipated).

Doing Russian and English tokenization with removed spaces makes the situation similar to Chinese with reasonable quality on lexicon-based tokenization but much worse results on TF-based one.

https://github.com/aigents/pygents

# Corpora and Methodology

**Train corpora**

**Chinese**
CLUE News 2016 Validation – 270M
CLUE News 2016 Train – 8,500M

**English**
Brown – 6M
Gutenberg Children – 29M
Gutenberg Adult – 140M
Social Media – 68M
All above – combined

**Russian**
RusAge Test – 141M
RusAge Previews – 825M

**Test corpus**

**Parallel Chinese/English/Russian** – 100 multi-sentence statements on finance

**Metrics/Indicators:**

Ngram (Character)
- Probability or Conditional Transition Probability (p-/p+)
  - Deviation (dvp-/dvp+)
  - Derivative (dp-/dp+)
- Transition Freedom (f-/f+)
  - Deviation (dvf-/dvf+)
  - Derivative (df-/df+)

**Hyper-parameters:**

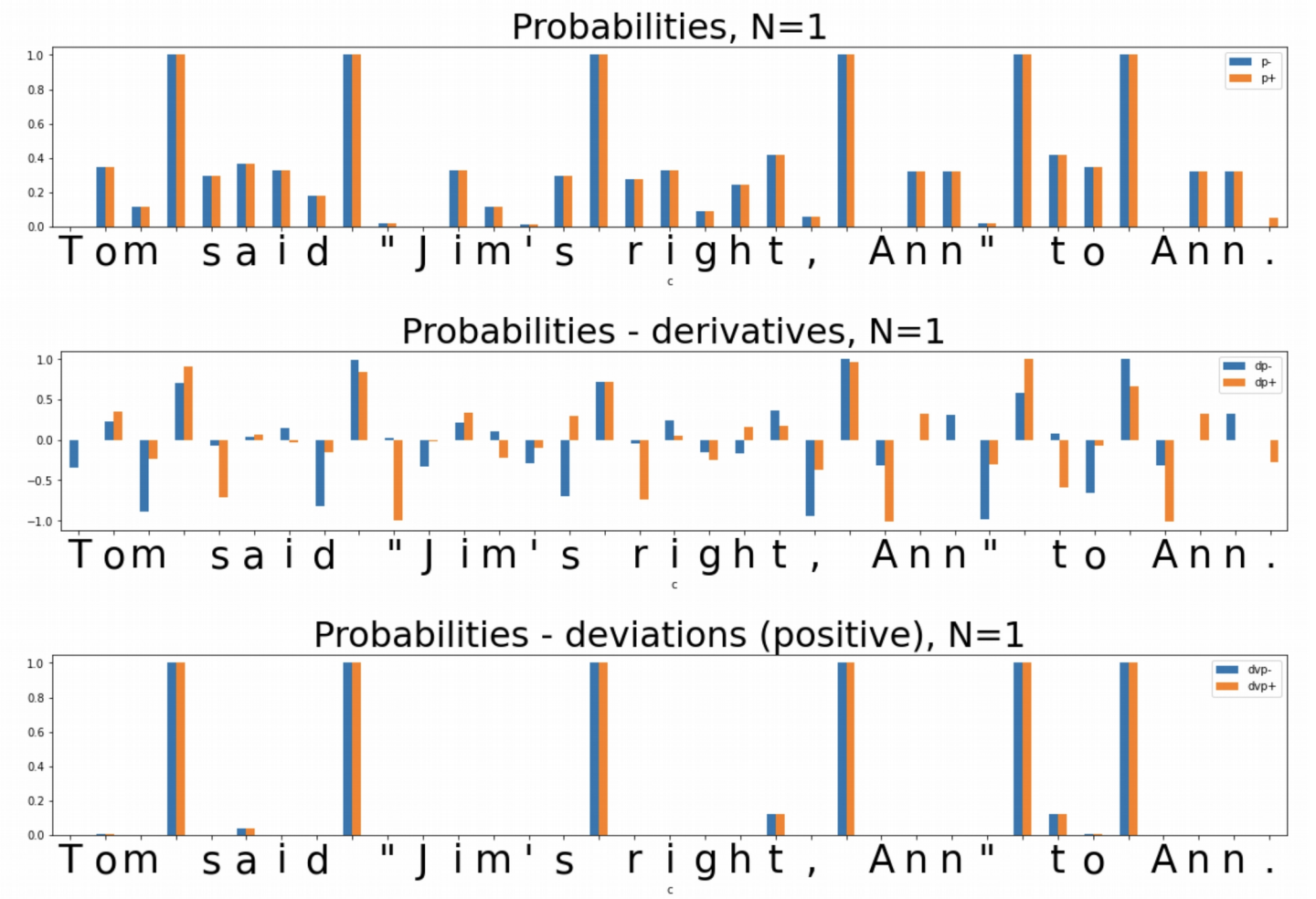
Combination of Ngram ranks N ([1],[2],[3],[1,2],[1,2,3],…)
Threshold for model compression
Threshold for segmentation

**Evaluations:**

Tokenization F1, on set of tokens found comparing to delimiter-based (English/Russian) or Jieba (Chineze)
Precision on set of tokens found comparing to reference lexicons

# Unsupervised Text Segmentation (Tokenization)

**Metrics/Indicators:**
Ngram (Character)
Probability



# Unsupervised Text Segmentation (Tokenization)

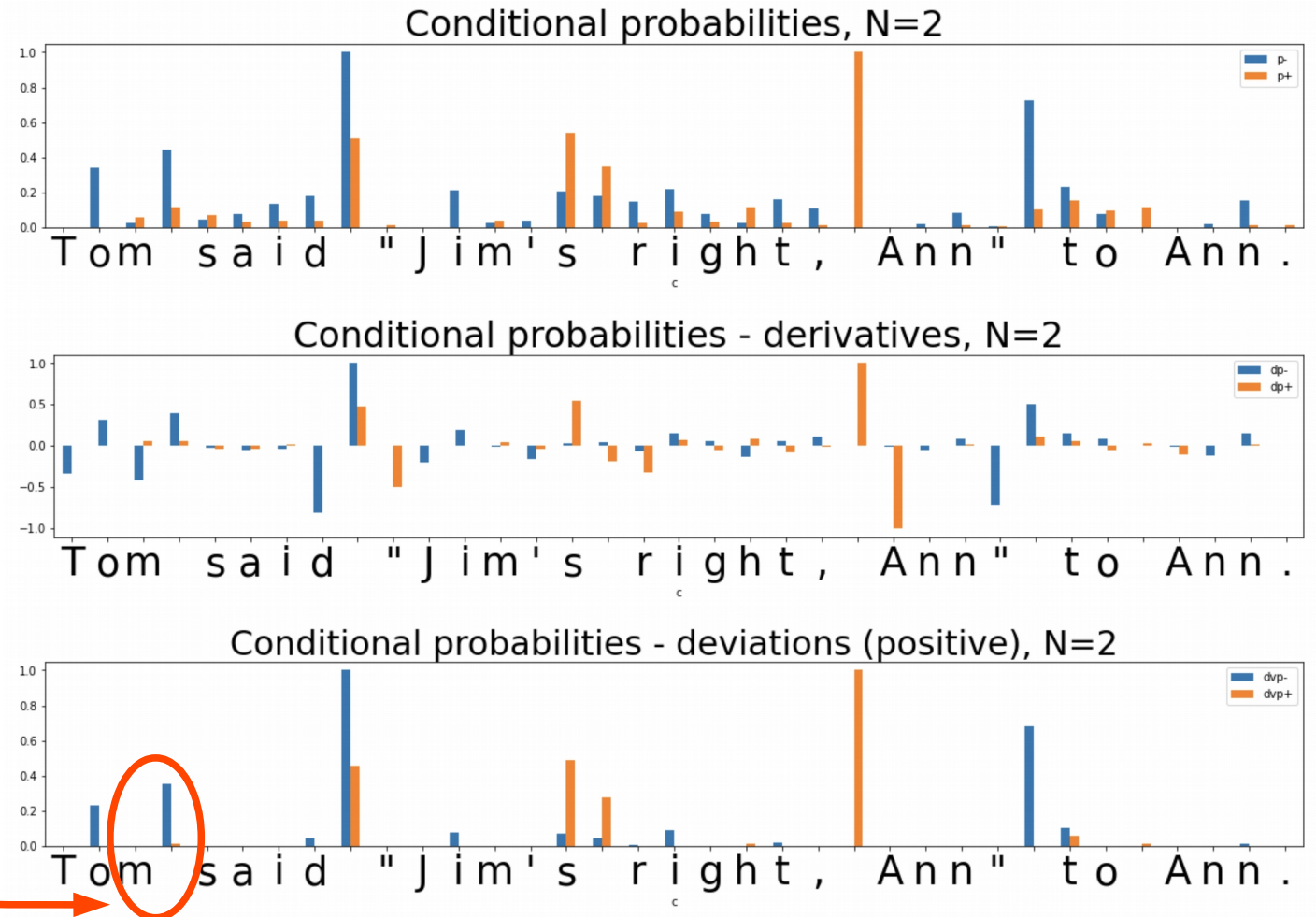
**Metrics/Indicators:**

Ngram (Character) Conditional Probability

(of Transition)

$P(Ngram_{n+1})/P(Ngram_n)$

P(“m ”)/P(“m”)



# Unsupervised Text Segmentation (Tokenization)

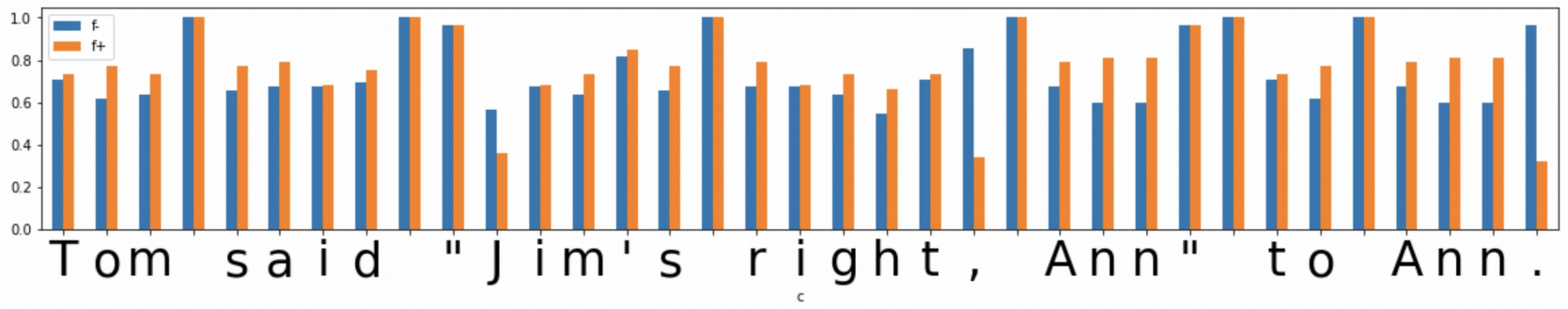
**Metrics/**

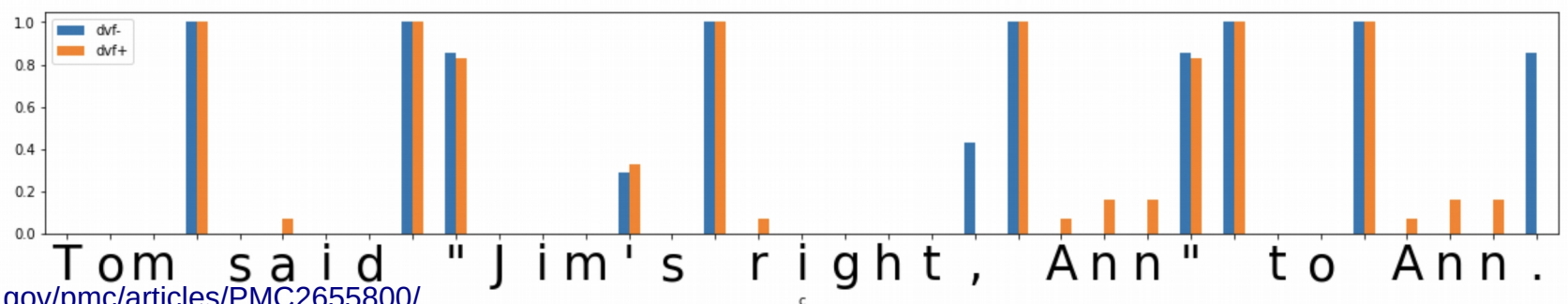
**Indicators:**

Transition Freedom Deviation

(Freedom of Transition)

```
Threshold 0.25
Tom said "Jim's right, Ann" to Ann.
['Tom', ' ', 'said', ' ', '"', "Jim's", ' ', 'right', ',', ' ', 'Ann', '"', ' ', 'to', ' ', 'Ann', '.']
['Tom', ' ', 'said', ' ', '"', 'Jim', "'", 's', ' ', 'right', ',', ' ', 'Ann', '"', ' ', 'to', ' ', 'Ann', '.']
0.89
Threshold 0.35
Tom said "Jim's right, Ann" to Ann.
['Tom', ' ', 'said', ' ', '"', "Jim's", ' ', 'right', ',', ' ', 'Ann', '"', ' ', 'to', ' ', 'Ann', '.']
['Tom', ' ', 'said', ' ', '"', "Jim's", ' ', 'right', ',', ' ', 'Ann', '"', ' ', 'to', ' ', 'Ann', '.']
1.0
```




https://www.ncbi.nlm.nih.gov/pmc/articles/PMC2655800/

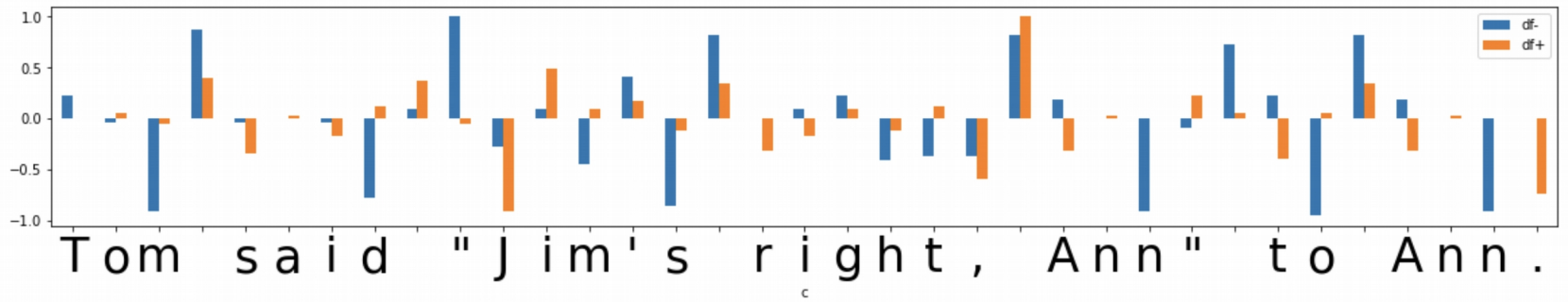
# Unsupervised Text Segmentation (Tokenization)

**Metrics/**

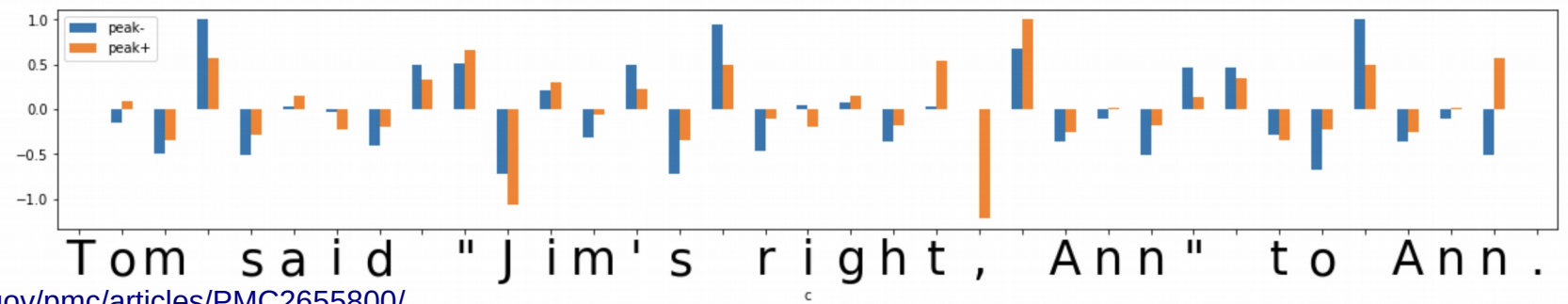
**Indicators:**

```
Threshold 0.25
Tom said "Jim's right, Ann" to Ann.
['Tom', ' ', 'said', ' ', '"', "Jim's", ' ', 'right', ',', ' ', 'Ann', '"', ' ', 'to', ' ', 'Ann', '.']
['Tom', ' ', 'said', ' ', '"', 'Ji', 'm', "'s", ' ', 'right', ',', ' ', 'Ann', '"', ' ', 'to', ' ', 'Ann', '.']
0.89
Threshold 0.35
Tom said "Jim's right, Ann" to Ann.
['Tom', ' ', 'said', ' ', '"', "Jim's", ' ', 'right', ',', ' ', 'Ann', '"', ' ', 'to', ' ', 'Ann', '.']
['Tom', ' ', 'said', ' ', '"', 'Jim', "'s", ' ', 'right', ',', ' ', 'Ann', '"', ' to', ' ', 'Ann', '.']
0.82
```

Transition Freedom Derivative and “Peak”




(Freedom of Transition “Peak”)




https://www.ncbi.nlm.nih.gov/pmc/articles/PMC2655800/

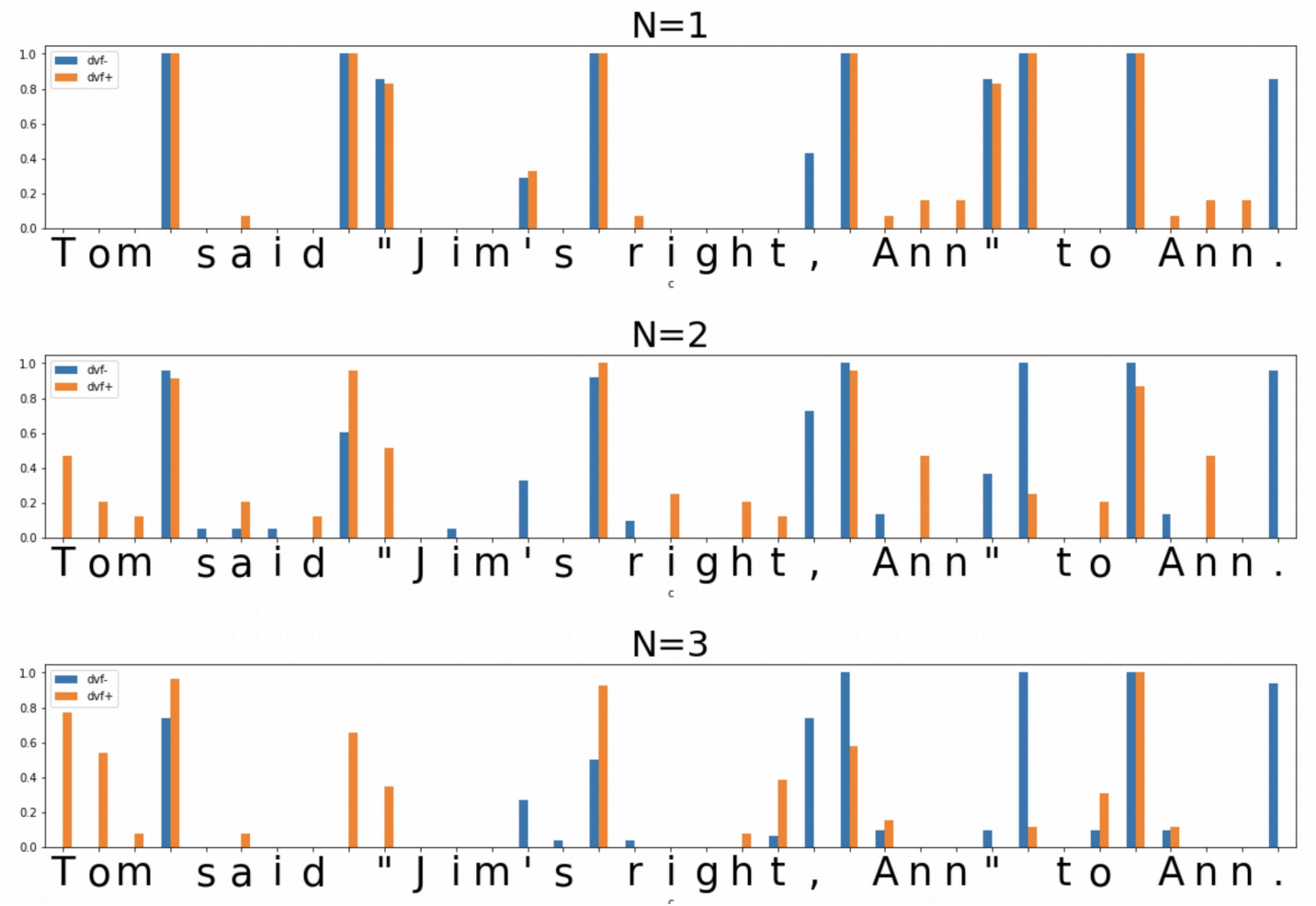
# Unsupervised Text Segmentation (Tokenization)

**Metrics/**

**Indicators:**

Transition
Freedom
Deviation

(varying “N”)



# Unsupervised Text Segmentation (Tokenization)

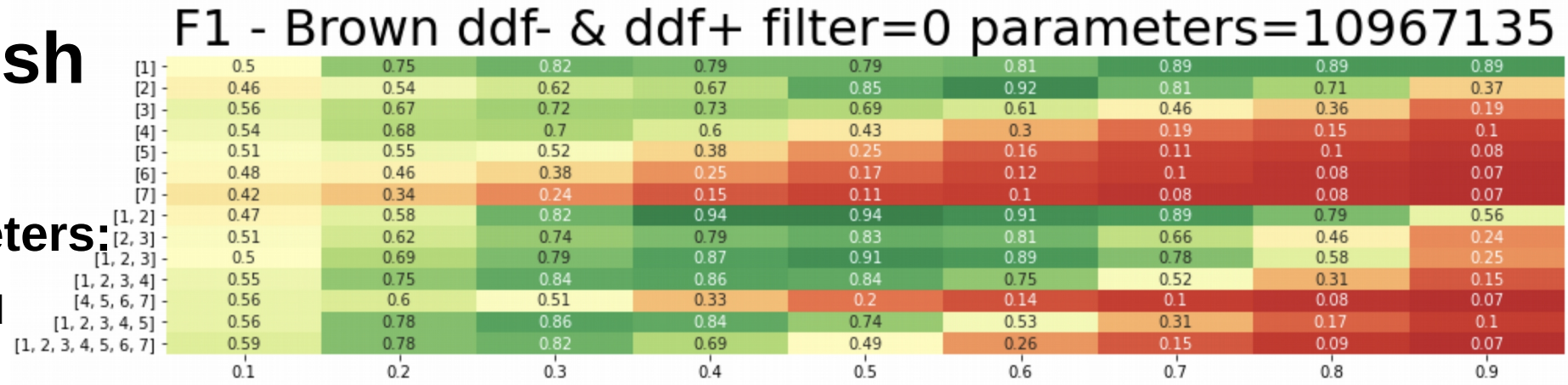
## English

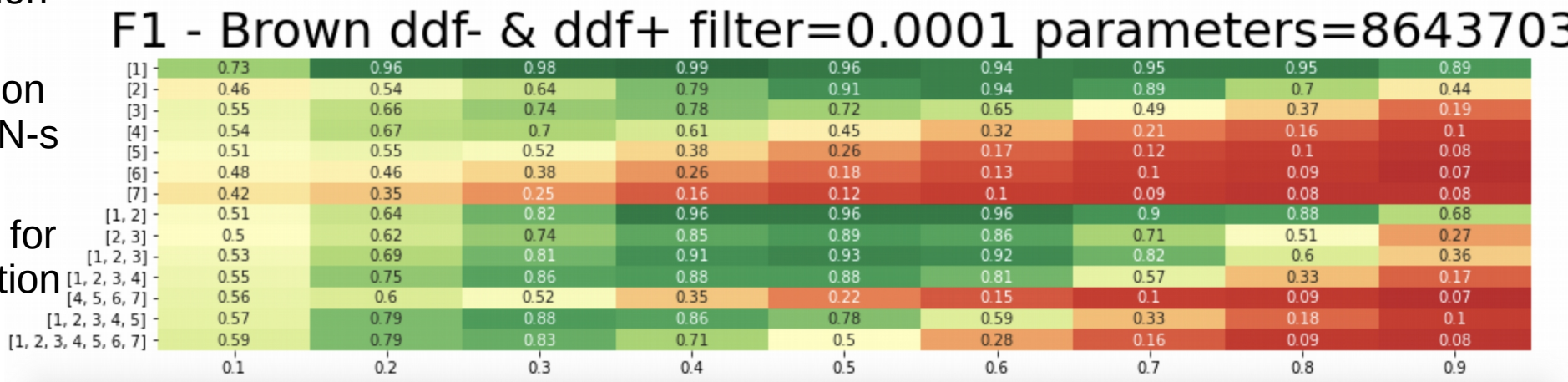
### Hyper-Parameters:

Threshold for model compression

Combination of Ngram N-s

Threshold for segmentation



# Unsupervised Text Segmentation (Tokenization)

## Chinese

**Hyper-**

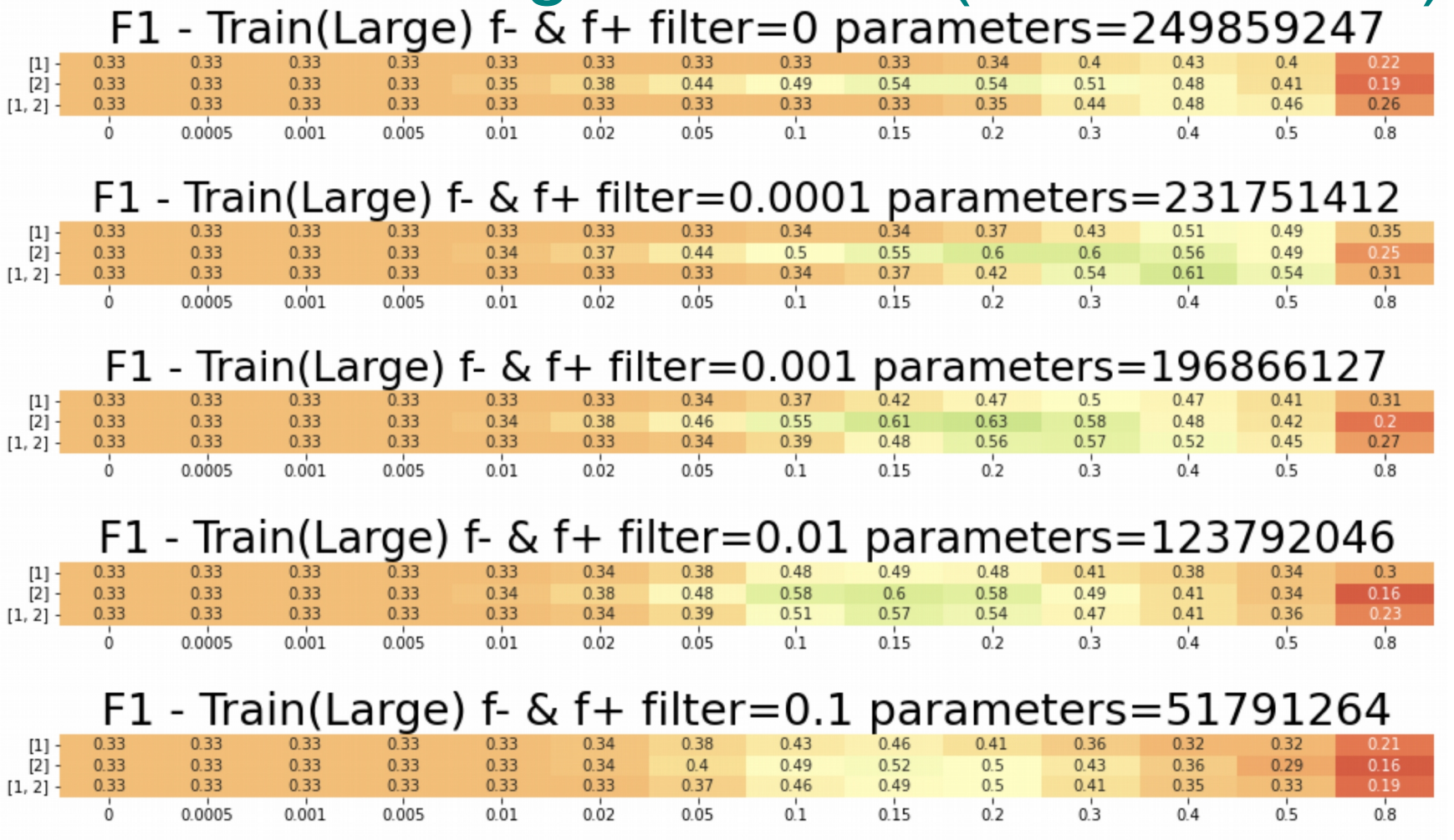
**Parameters:**

TF

Threshold for model compression

Combination of Ngram N-s

Threshold for segmentation



# Unsupervised Text Segmentation (Tokenization)

## Chinese

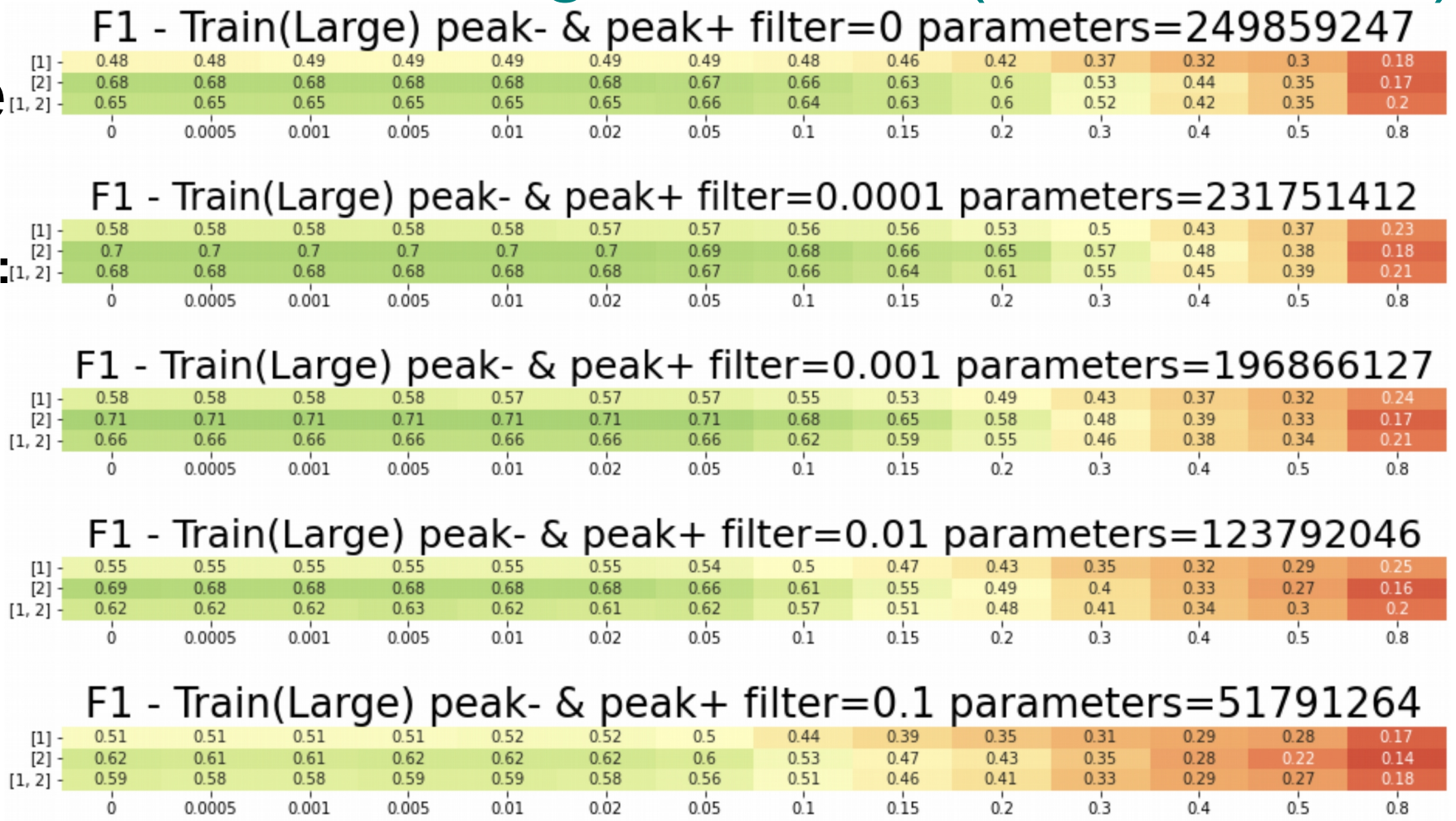
### Hyper-Parameters:

“Peak”

Threshold for model compression

Combination of Ngram N-s

Threshold for segmentation



# Unsupervised Text Segmentation (Tokenization)

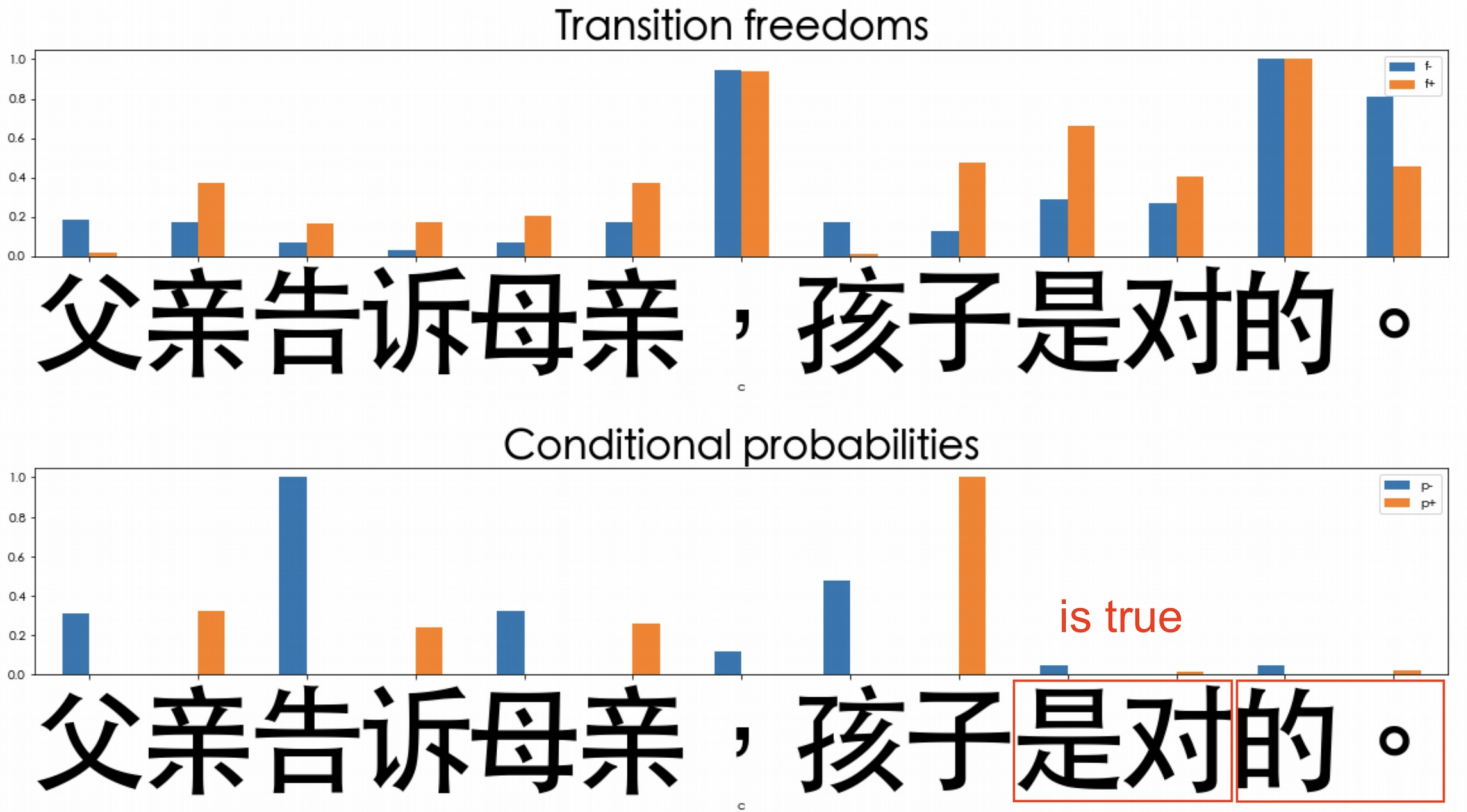
```
The father told the mother that the child was right.
Threshold  0.15
父亲告诉母亲，孩子是对的。
['父亲', '告诉', '母亲', ', ', '孩子', '是', '对', '的', '。']
['父亲', '告诉', '母亲', ', ', '孩子', '是', '对', '的', '。']
1.0
```

**Metrics/Indicators:**

Transition Freedom Deviation

Conditional Probability

(of Transition)



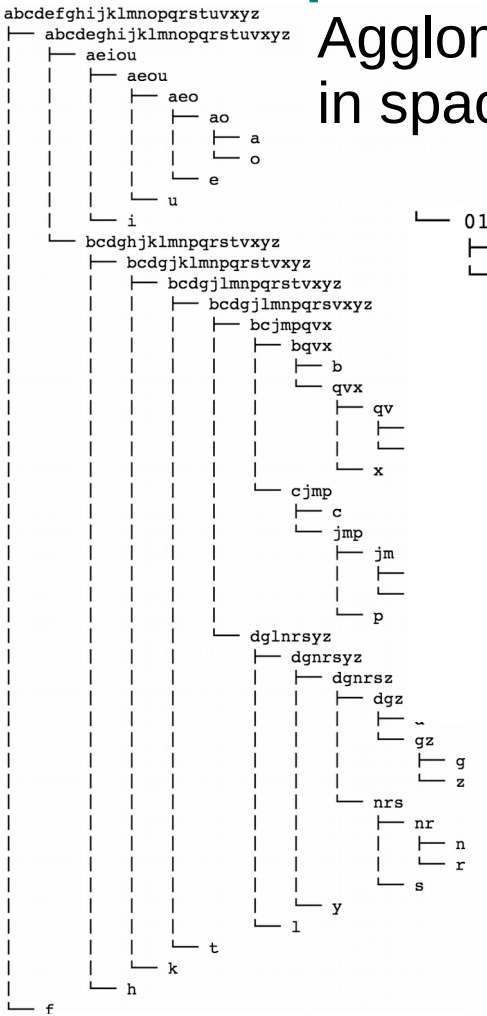
# Results – Freedom-based Tokenization against Lexicon

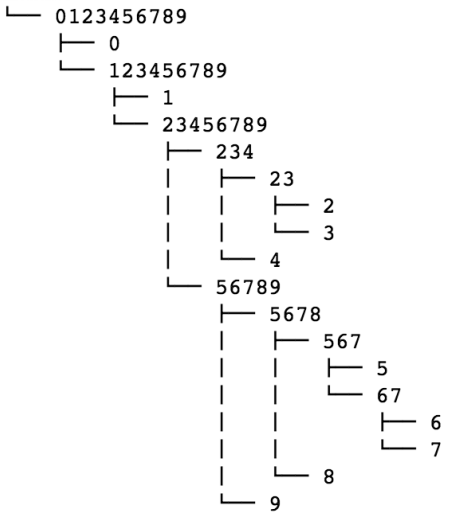
| Language | Tokenizer | Tokenization F1 | Lexicon Discovery Precision |
|---|---|---|---|
| English | Freedom-based | **0.99** | **0.99** (vs 1.0) |
| English | Lexicon-based | 0.99 | - |
| English no spaces | Freedom-based | 0.42 | - |
| English no spaces | Lexicon-based | 0.79 | - |
| Russian | Freedom-based | **1.0** | **1.0** (vs 1.0) |
| Russian | Lexicon-based | 0.94 | - |
| Russian no spaces | Freedom-based | 0.26 | - |
| Russian no spaces | Lexicon-based | 0.72 | - |
| Chinese | Freedom-based | **0.71** | **0.92** (vs 0.94) |
| Chinese | Lexicon-based | 0.83 | - |

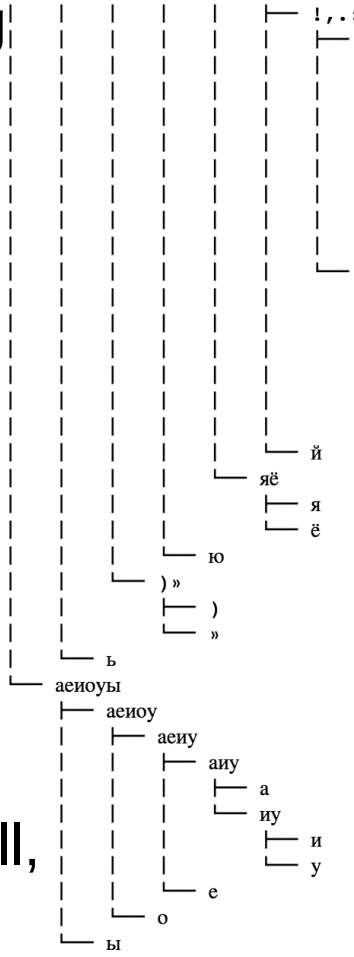
*Lexicon-based Tokenization - greedy/beam search on word length (optimal) or frequency*

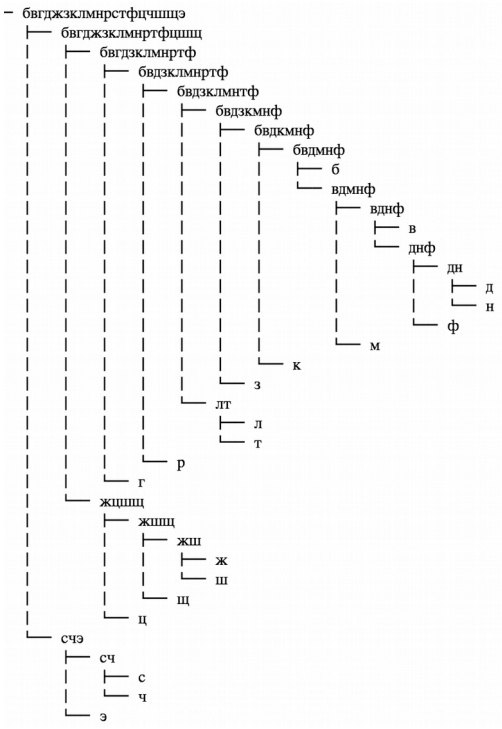
# Unsupervised Character Category Learning

Agglomerative Clustering
in space of Transitions



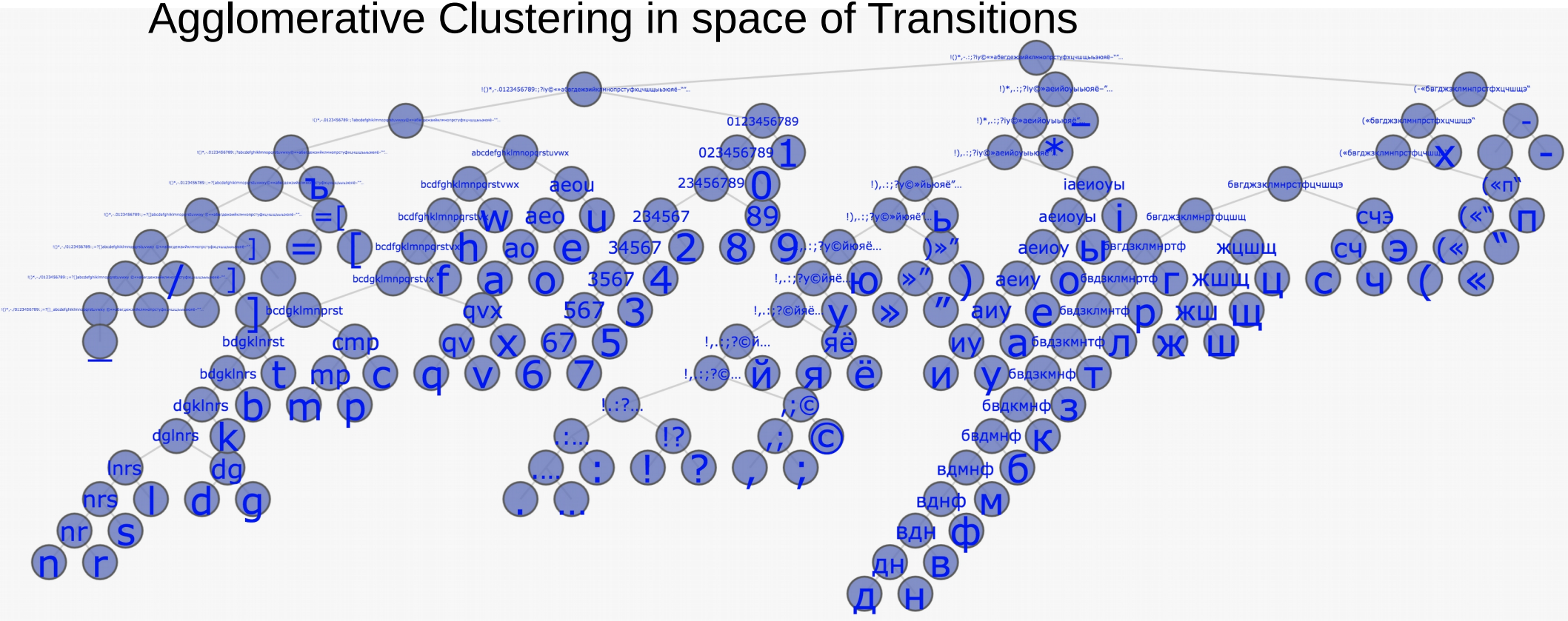




RusAge Test/Small,
Cosine Similarity

# Unsupervised Character Category Learning

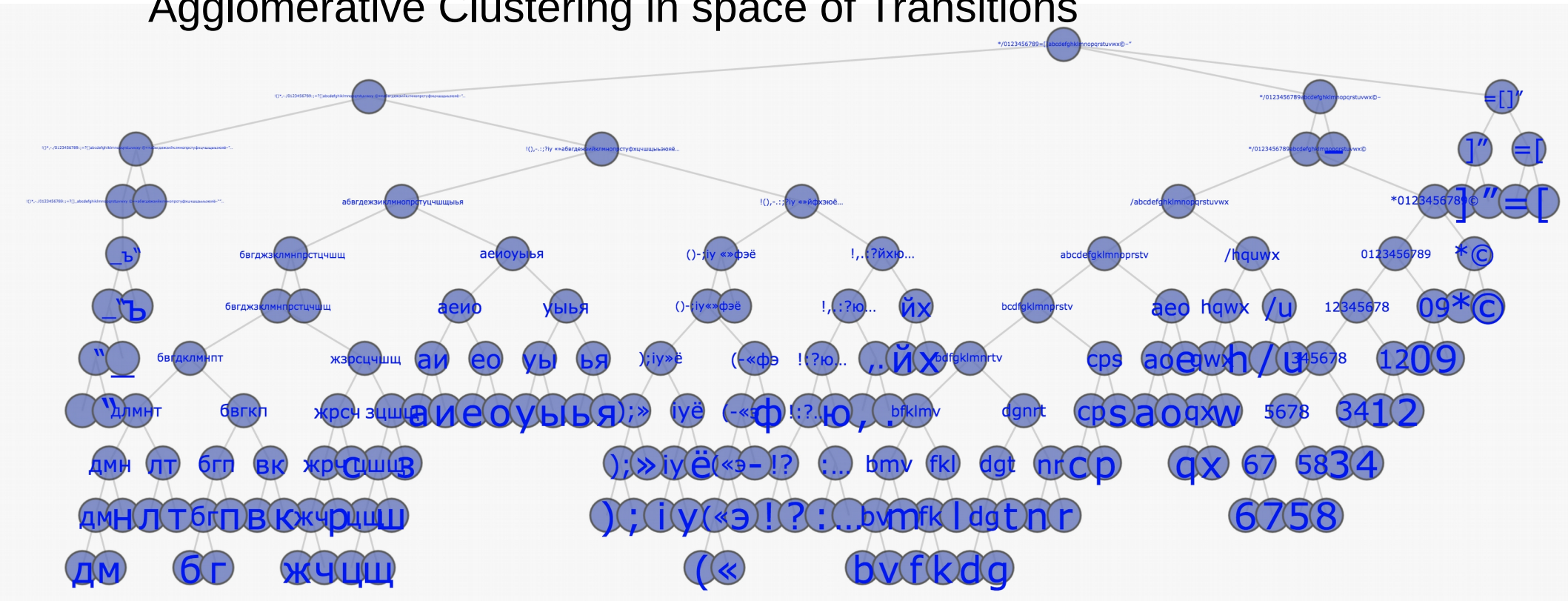
## Agglomerative Clustering in space of Transitions



RusAge Previews/Full, Cosine Similarity

# Unsupervised Character Category Learning

Agglomerative Clustering in space of Transitions



RusAge Previews/Full, Jackard Similarity

# Conclusion and Further Work

Unsupervised Tokenization based on Transition Freedom (TF) recall and precision appears good enough as initial approximation for further applications of self-reinforcement learning as part of interpretable unsupervised learning of natural language.

Optimal thresholds and specific TF-based metrics are specific to language. The process and policy of their discovery and adjustment should be further explored.

Clustering or parts of speech on space of transition graphs may provide some insights on morphology and punctuation structure of low-resource and domain-specific languages.

Hybridization of TF-based tokenization approach with lexicon-based one might be efficient for low-resource and domain-specific languages.

Further unsupervised grammar learning experiments can be run on the basis of suggested unsupervised tokenization approach.

Applications for other Experiential Learning environments, including the ones with delayed/sparse feedback.

Using Reinforcement Learning techniques with self-reinforcement on historical data under Unsupervised Learning setup.

https://github.com/aigents/pygents

# Applications other than NLP and Experiential/Reinforcement Learning

## Everything is a Process of a Scenario!

https://arxiv.org/abs/1807.02072

| | **Spoken language recognition** | **Written language recognition** | **Identification of patterns in the text** | **Causal analysis** |
|---|---|---|---|---|
| **Actor** | Coefficient on spectrogram for particular frequency | Property of specific stroke:<br>On the top, at the bottom, long, short, skewed, etc. | Object property value:<br>Name “John” | Specific actor:<br>John Doe |
| **Event** | Combination of coefficients on spectrogram | Period or stroke composing the letter:<br>. | Object class instance:<br>Name “John”, surname “Doe” | Specific event:<br>John Doe cleaning the window on the second floor. |
| **Coincidence** | Specific sound | Coincidence:<br>i | Co-occurrence of object of class person properties:<br>“John Doe” | Specific coincidence:<br>Window on the second floor is dirty, John Doe is cleaning it. |
| **Process** | Specific spoken word | Specific written word:<br>ping | Specific phrase:<br>“John Doe cleans the window” | Specific process:<br>Window on the second floor was dirty, John Doe has cleaned it and now it is clean. |
| **Role** | Pitch frequency | Property of symbol: orientation, extent, symmetry, etc. | Domain of the object class property:<br>person’s surname | Typical role:<br>Cleaner |
| **Appearance** | Spectral cluster on the spectrogram | Element of symbol:<br>. | Class of the variable object:<br>person | Typical appearance:<br>Someone cleaning something |
| **Situation** | Sound of speech | Symbol:<br>i | Pattern variable:<br>$subject | Typical situation:<br>Someone is cleaning something which is dirty. |
| **Scenario** | Spoken word accordingly to the language model | Written word:<br>ping | Phrase pattern:<br>“$subject cleans $object” | Typical scenario:<br>Something was dirty, someone has cleaned it, it is clean now. |

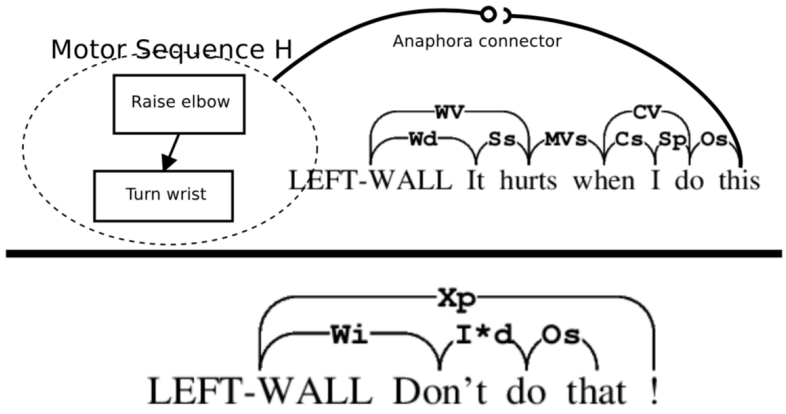
# Text Grounding on Non-Text Events

## Common Sense Reasoning

Everything is a Graph and can be coded with Link Grammar!

Rules, laws, axioms of reasoning and inference can be learned.

$$\frac{A \wedge A \rightarrow B}{B}$$




Naively, simplistically: Learned Stimulus-Response AI (SRAI)[9]

Linas Veptstas, 2021

https://aigents.github.io/inlp/2021/slides/

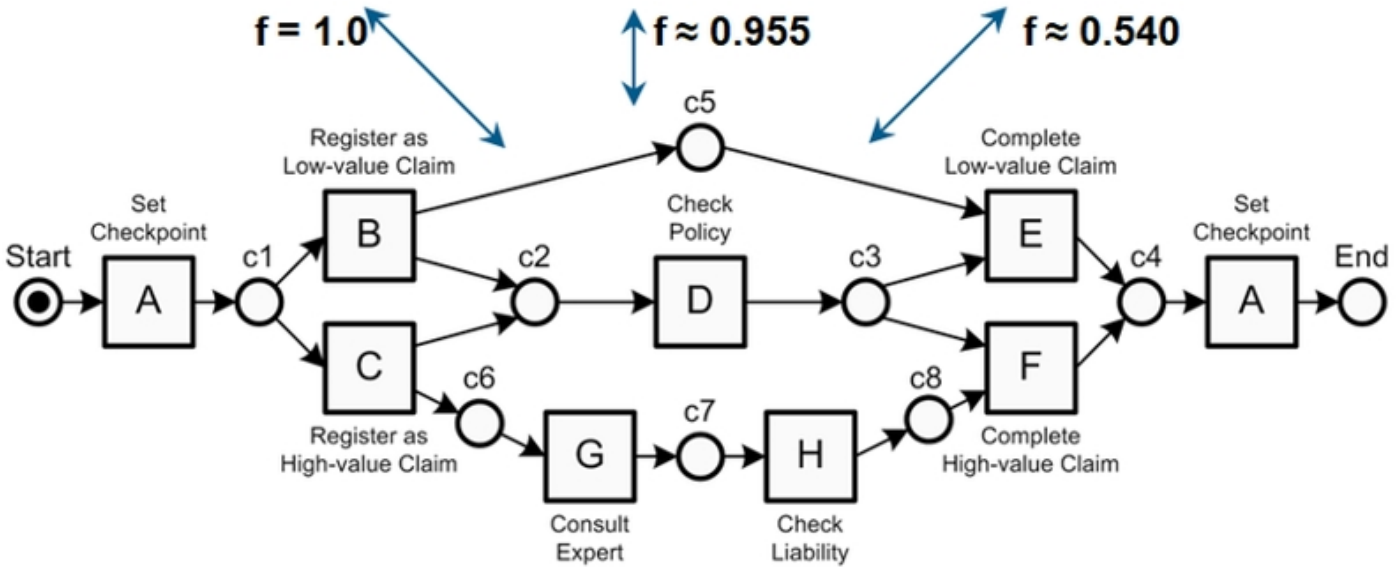
[9] Metaphorical example: Mel'čuk's Meaning Text Theory (MTT) SemR + Lexical Functions (LF) would be better.

# Process Mining in Business Log Data

| No. of Instances | Log Traces |
|---|---|
| 4070 | ABDEA |
| 245 | ACDGHFA |
| 56 | ACGDHFA |

| No. of Instances | Log Traces |
|---|---|
| 1207 | ABDEA |
| 145 | ACDGHFA |
| 56 | ACGDHFA |
| 23 | ACHDFA |
| 28 | ACDHFA |

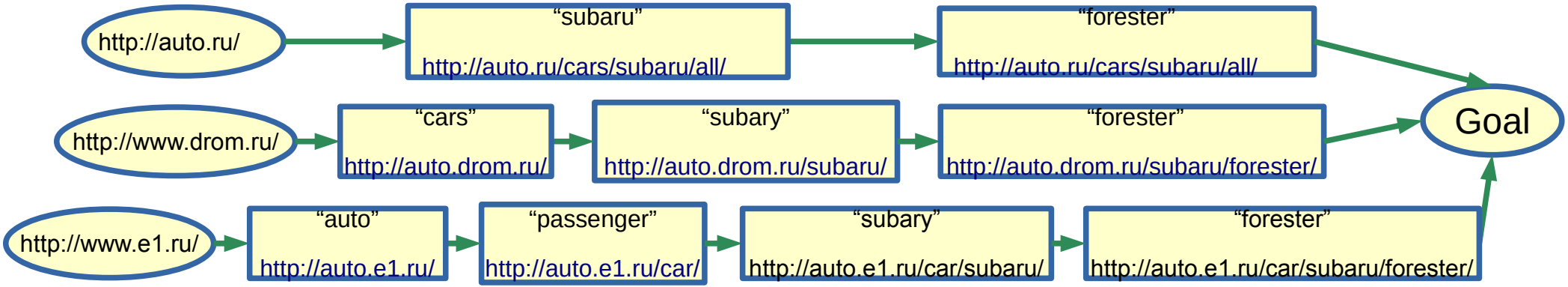
| No. of Instances | Log Traces |
|---|---|
| 24 | BDE |
| 7 | AABHF |
| 15 | CHF |
| 6 | ADBE |
| 1 | ACBGDFAA |
| 8 | ABEDA |



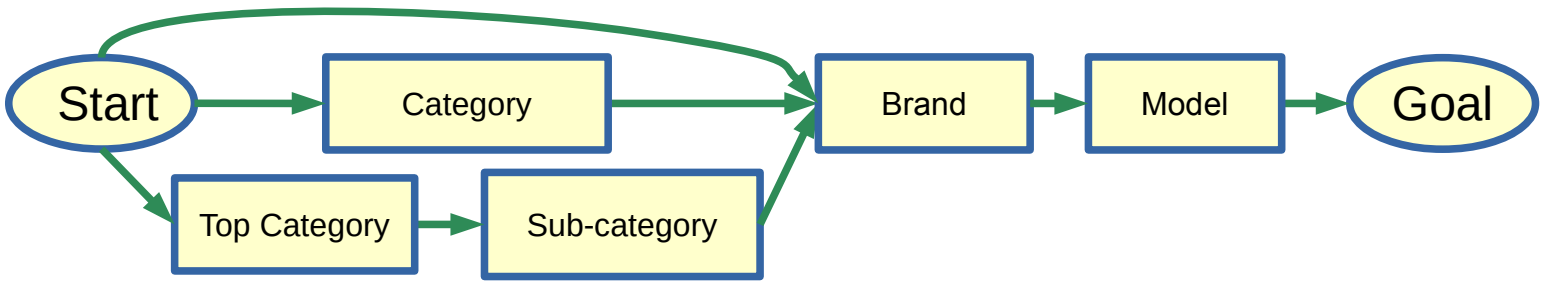

https://www.puzzledata.com/process-mining_eng/

# Scenario Mining in Process Data Example

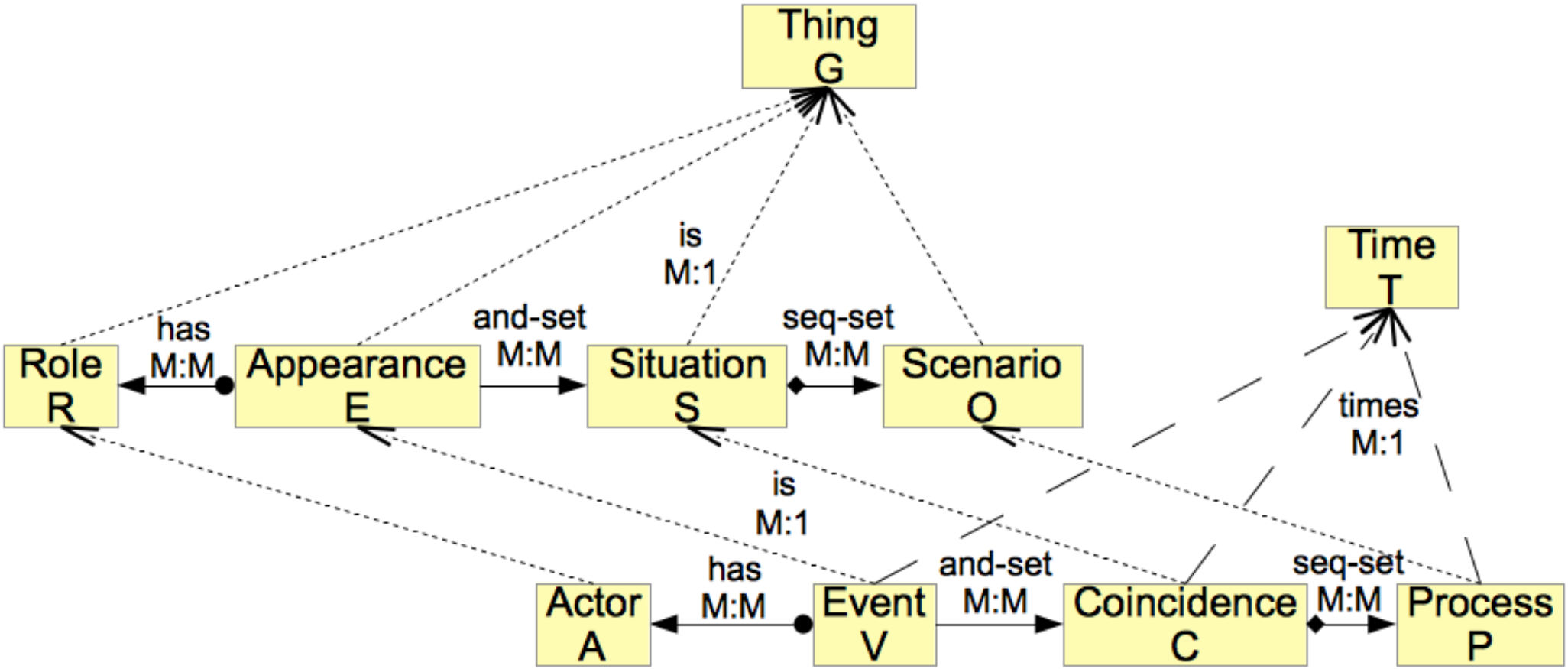
Internet navigation routes when searching for “Forester” cars




Generalized click-through scenario when searching for products

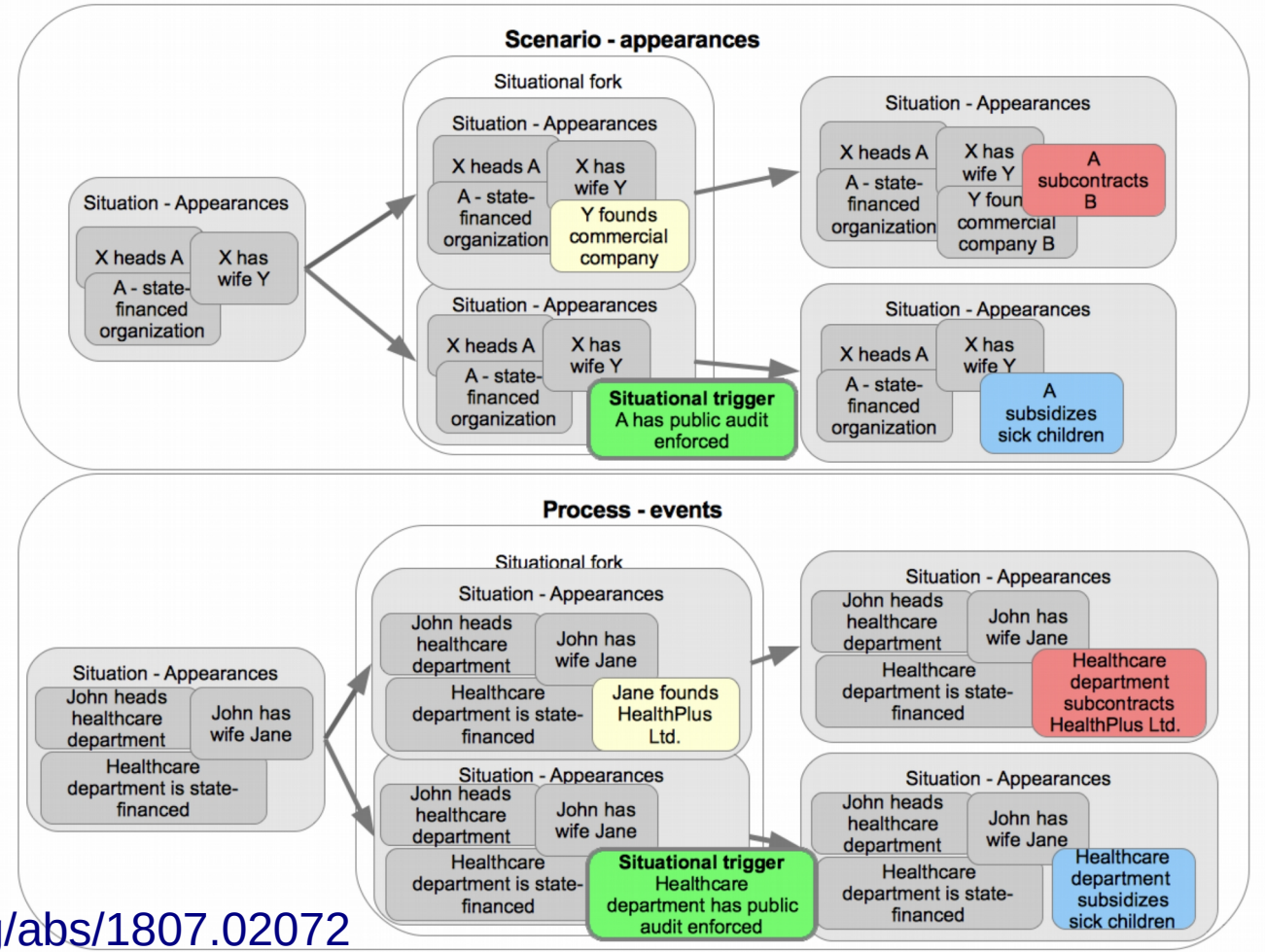


# Foundation (Generic) Activity Ontology




https://arxiv.org/abs/1807.02072

# Upper (Domain) Activity Ontology Example

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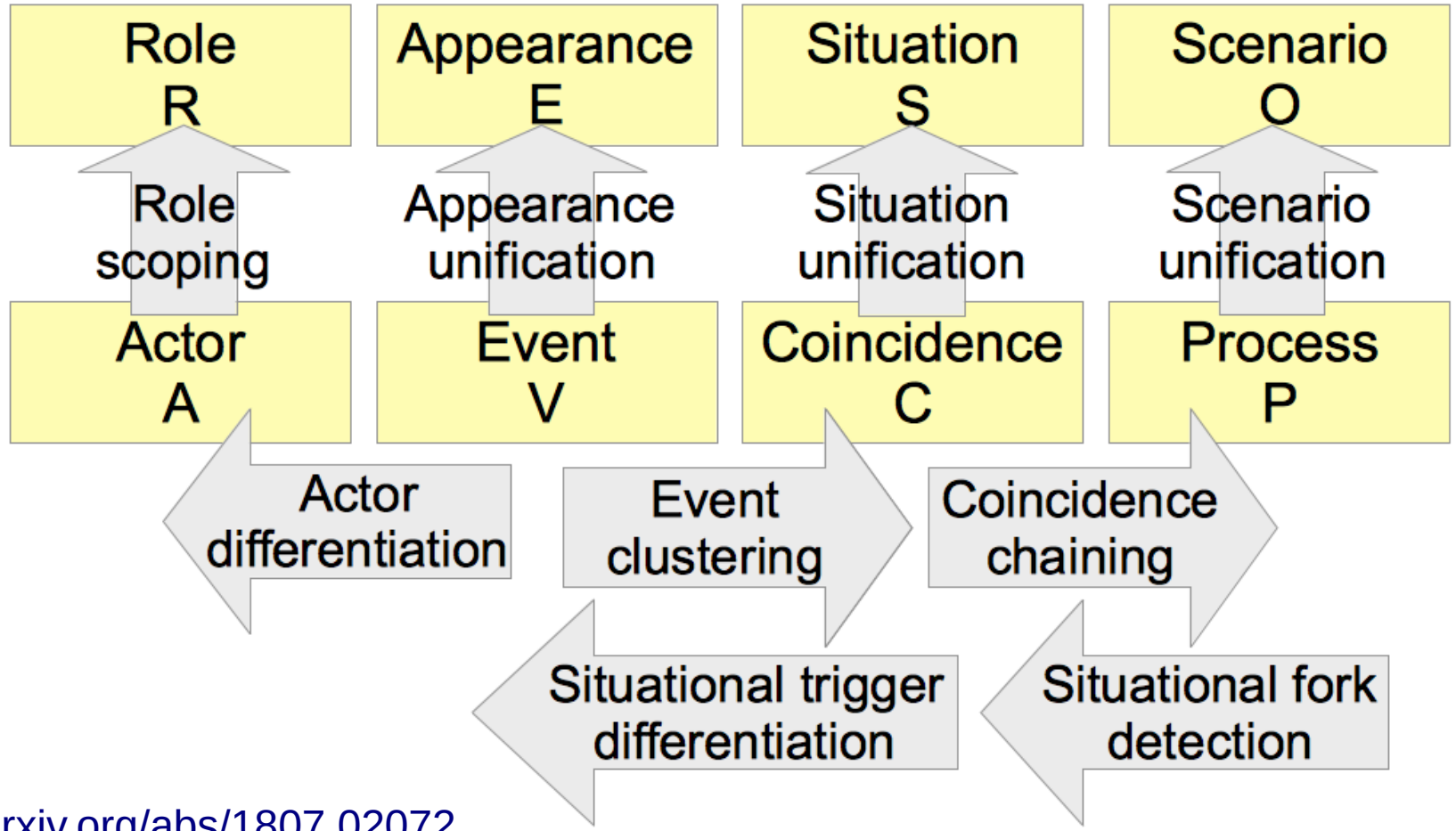
# Scenario Mining in Process Data

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# Thank you and welcome!


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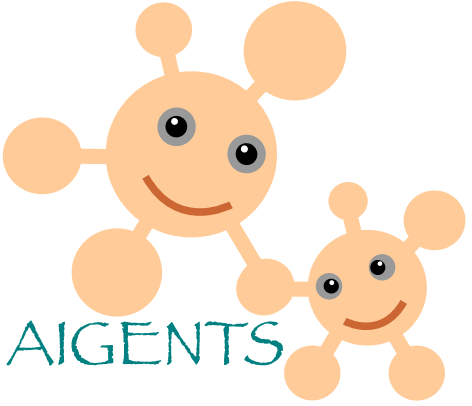


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