

Unsupervised Clustering and Segmentation – why and how?

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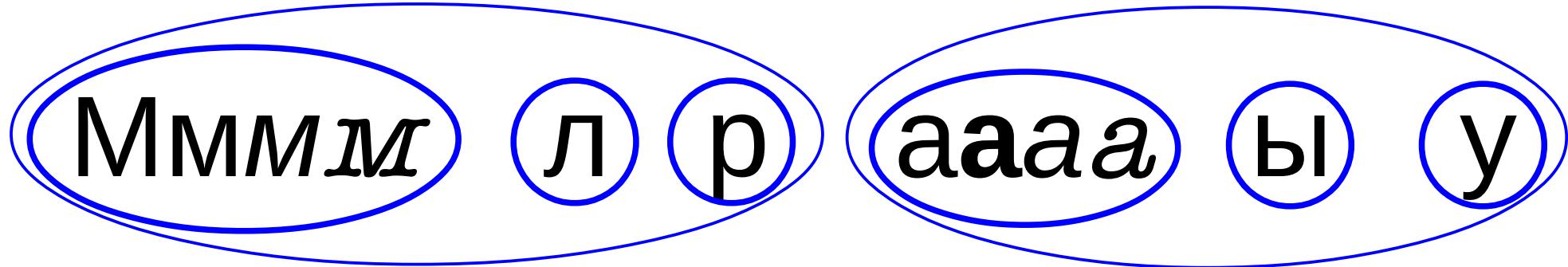
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<https://agirussia.org>

Clustering and Segmentation



Motivation

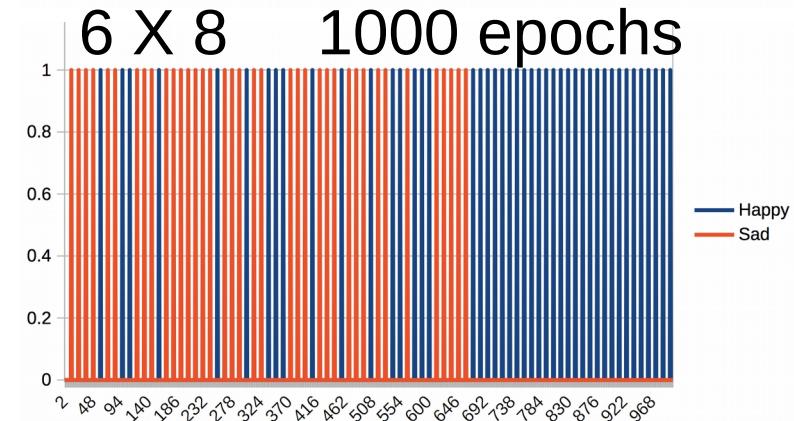
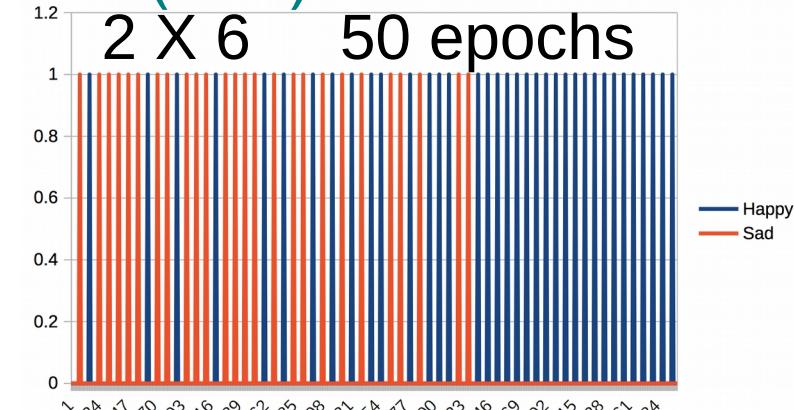
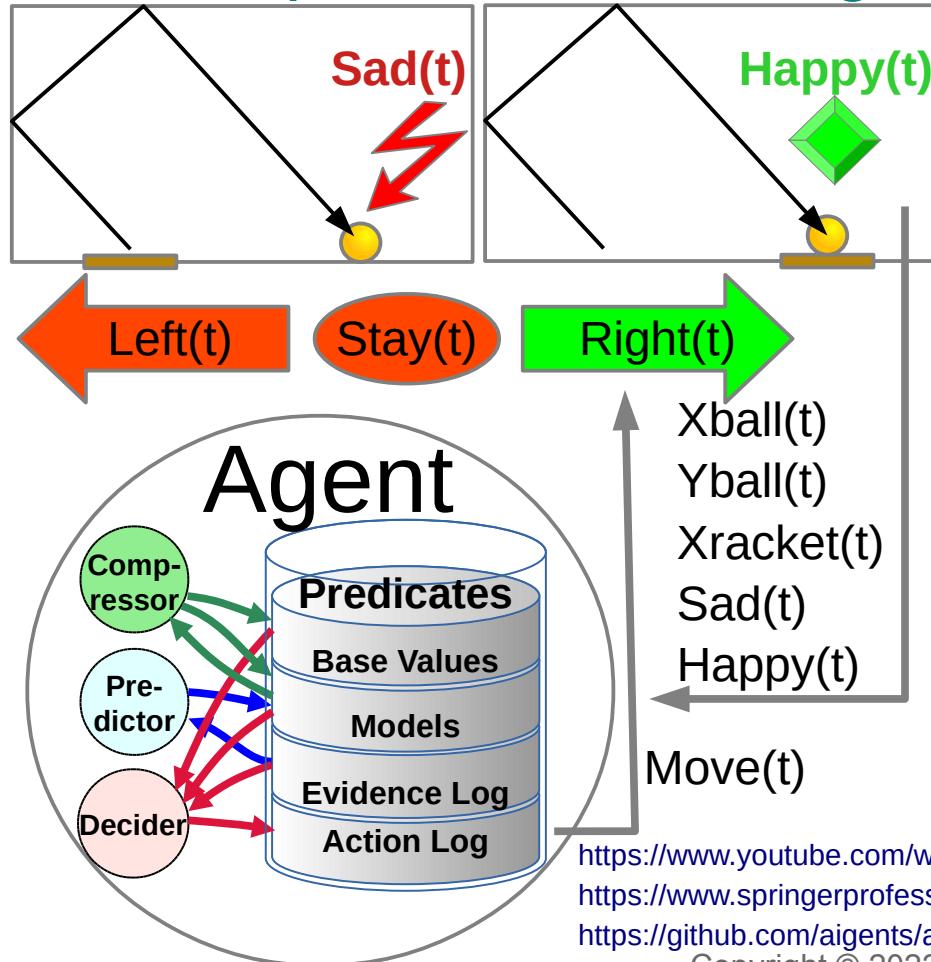
Identifying successful/unsuccessful sequential experiences for experiential learning for global (self)reinforcement

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

<https://arxiv.org/abs/2205.11443>
<https://github.com/aigents/pygents>

Unsupervised Learning of Temporal Abstractions with Slot-based Transformers
Anand Gopalakrishnan, Kazuki Irie, Jürgen Schmidhuber, Sjoerd van Steenkiste
<https://arxiv.org/abs/2203.13573>

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

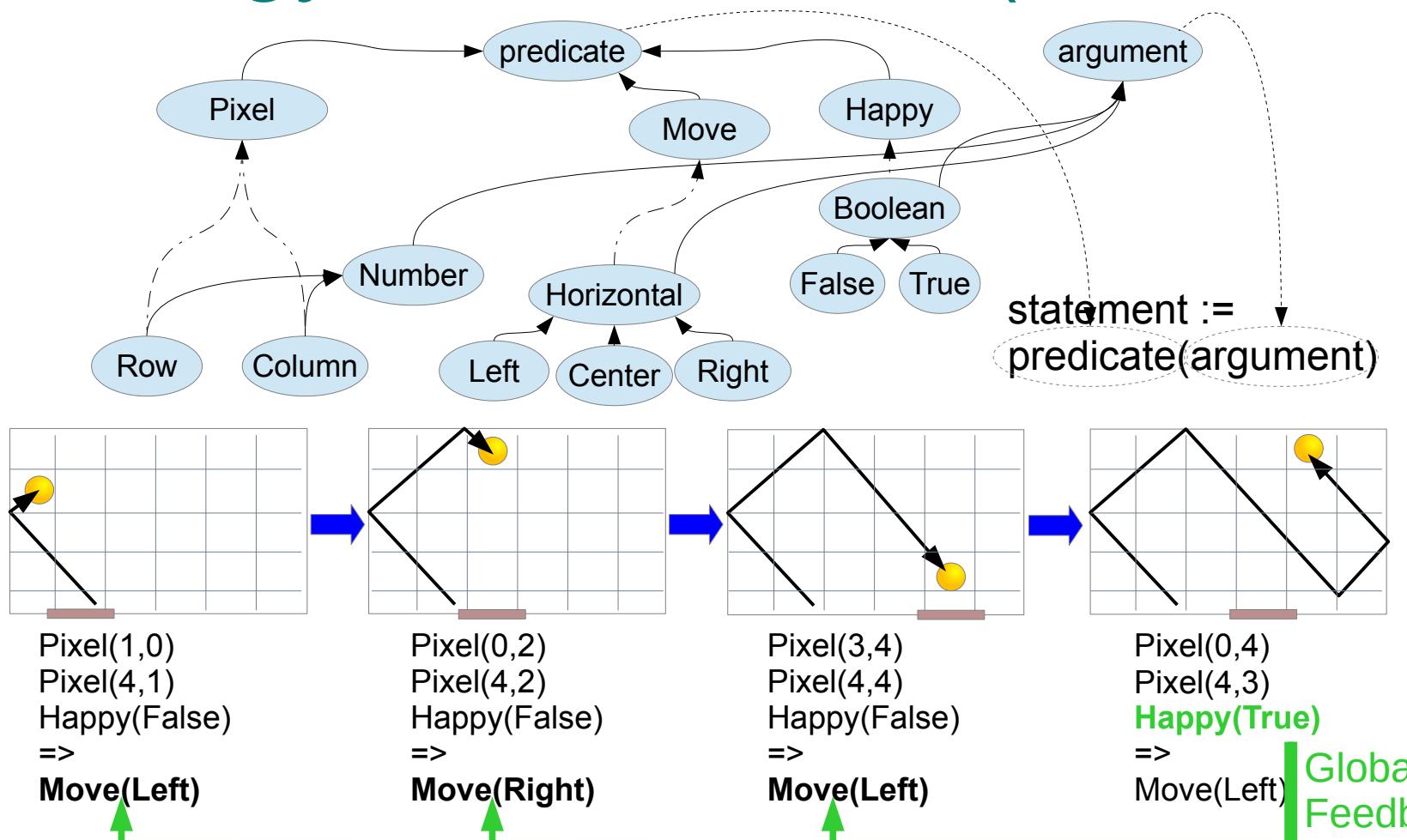


<https://www.youtube.com/watch?v=2LPLhJKh95g>

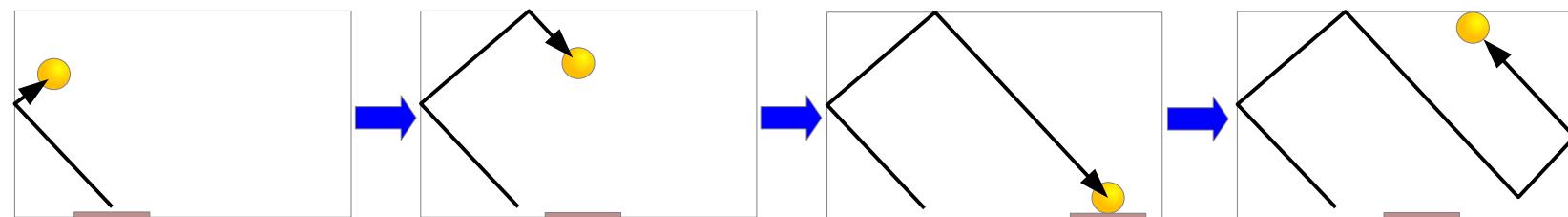
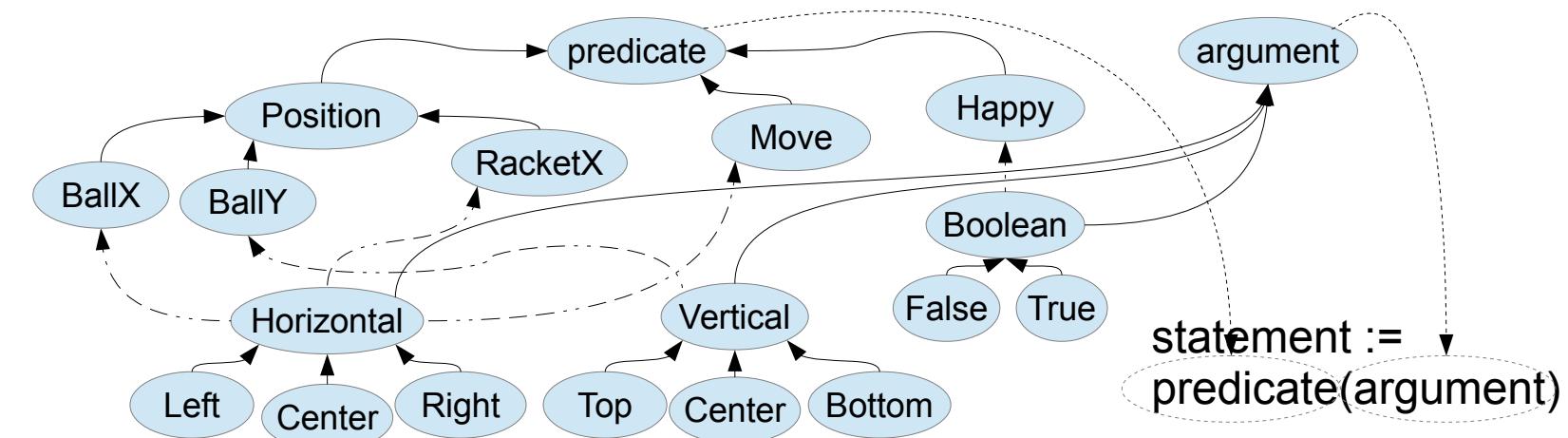
<https://www.springerprofessional.de/neuro-symbolic-architecture-for-experiential-learning-in-discret/20008336>

<https://github.com/aigents/aigents-java/tree/master/src/main/java/net/webstructor/agj>

Ontology and Grammar (“Discrete”)



Ontology and Grammar (“Symbolic”)



BallY(Top)
BallX(Left)
RacketX(Left)
Happy(False)
=> **Move(Left)**

BallY(Top)
BallX(Center)
RacketX(Center)
Happy(False)
=> **Move(Right)**

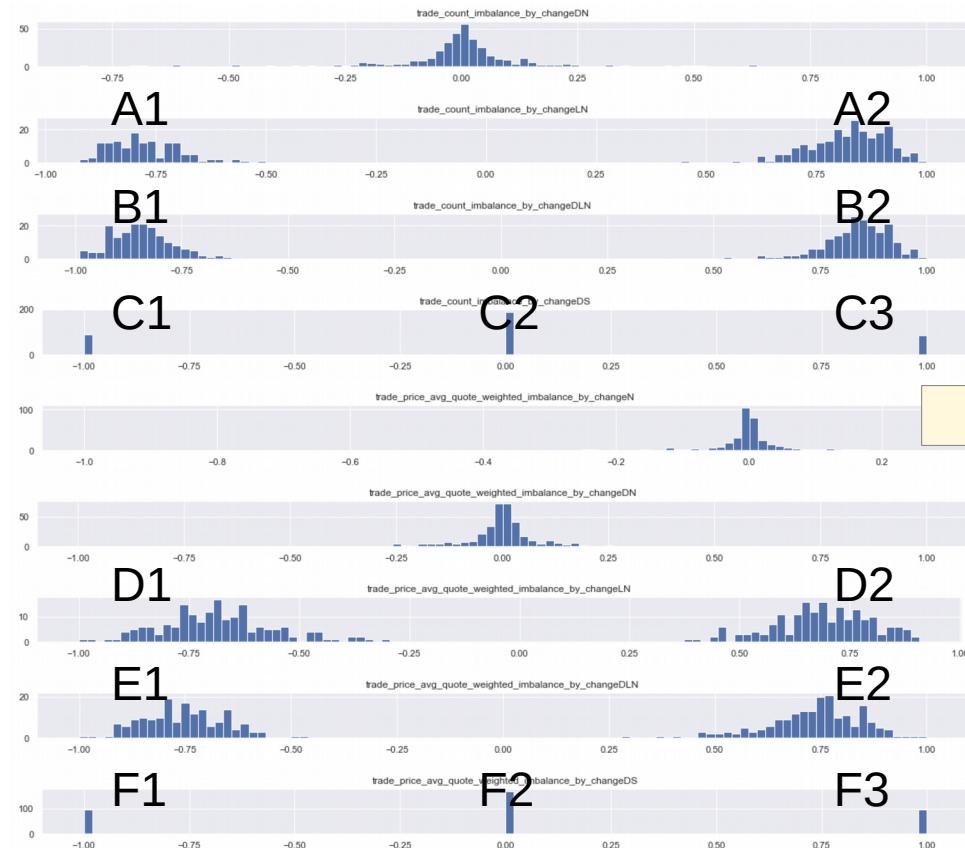
BallY(Bottom)
BallX(Right)
RacketX(Right)
Happy(False)
=> **Move(Right)**

BallY(Bottom)
BallX(Right)
RacketX(Right)
Happy(True)
=> **Move(Left)**

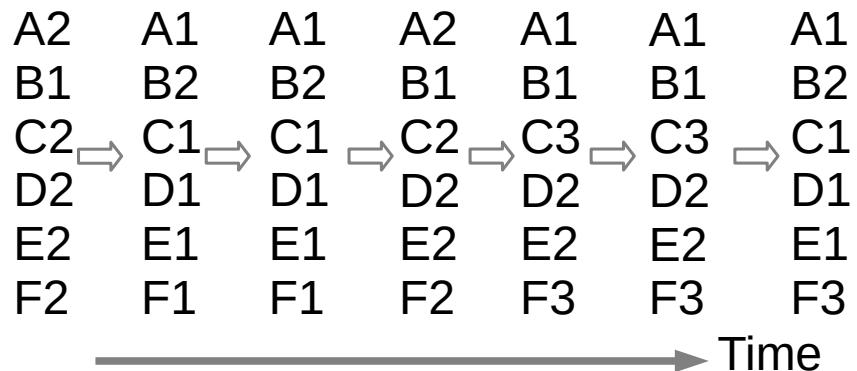
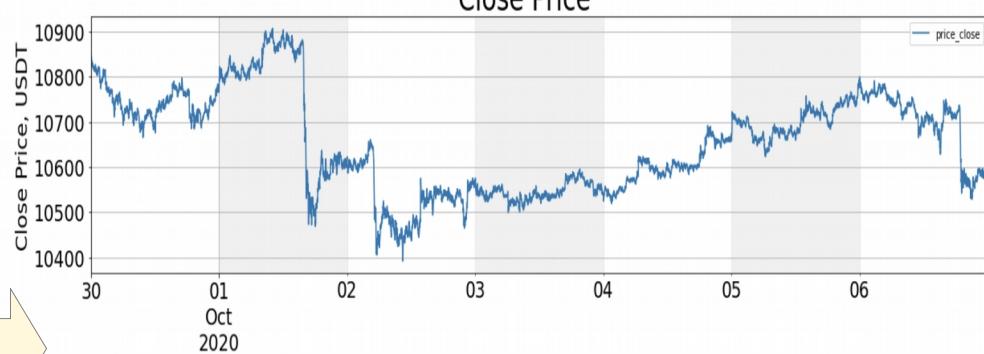
Global
Feedback

“Symbolizing” Market Conditions

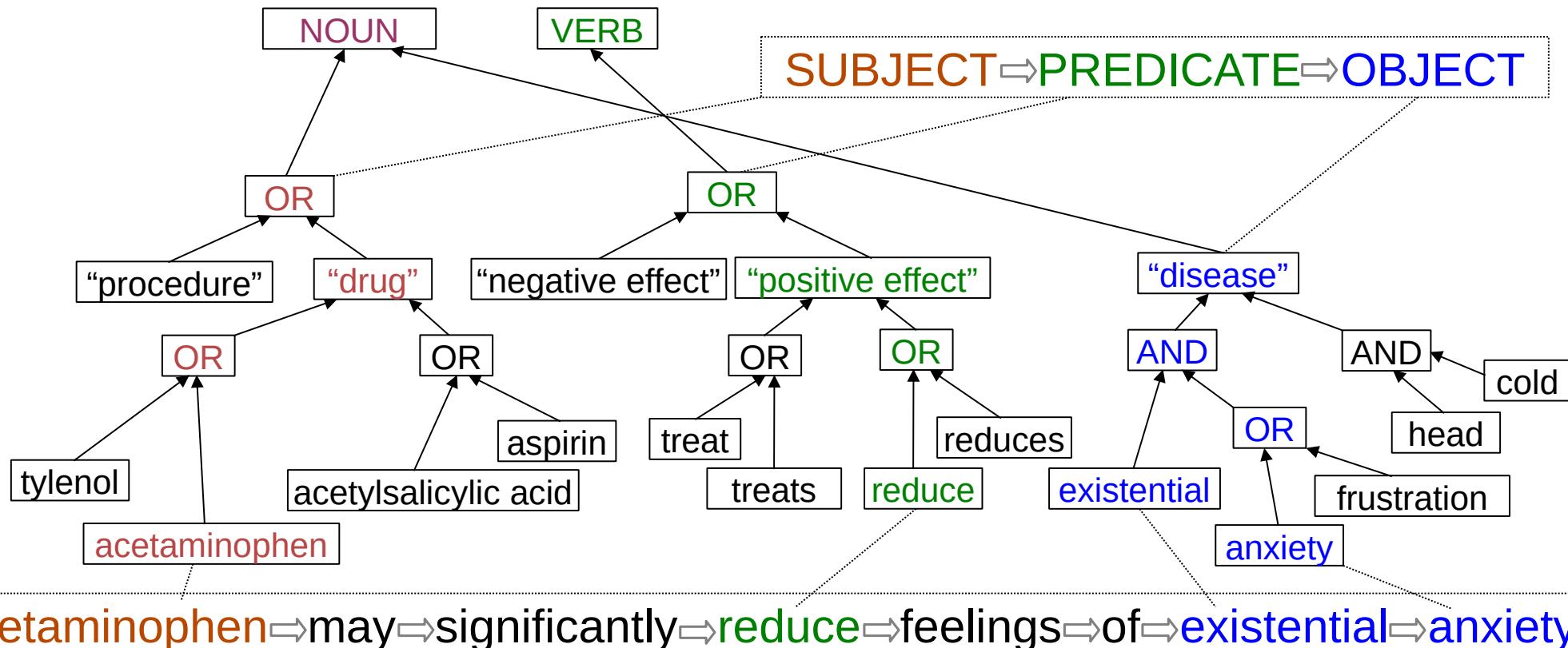
Quantifying Time Series Metrics



Flat Crash Crash Flat Up Up Crash



Discovering NLP patterns such as words or phrase structures for unsupervised language learning (Aigents® “Deep Patterns”)



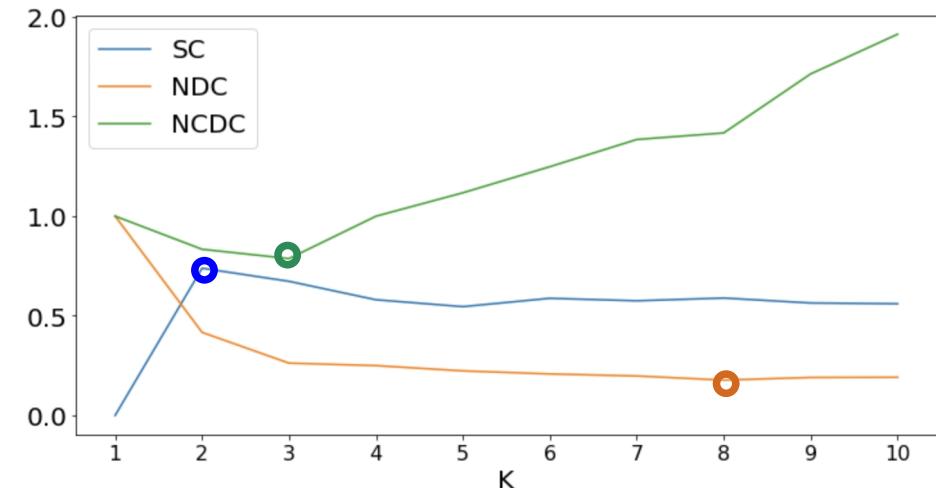
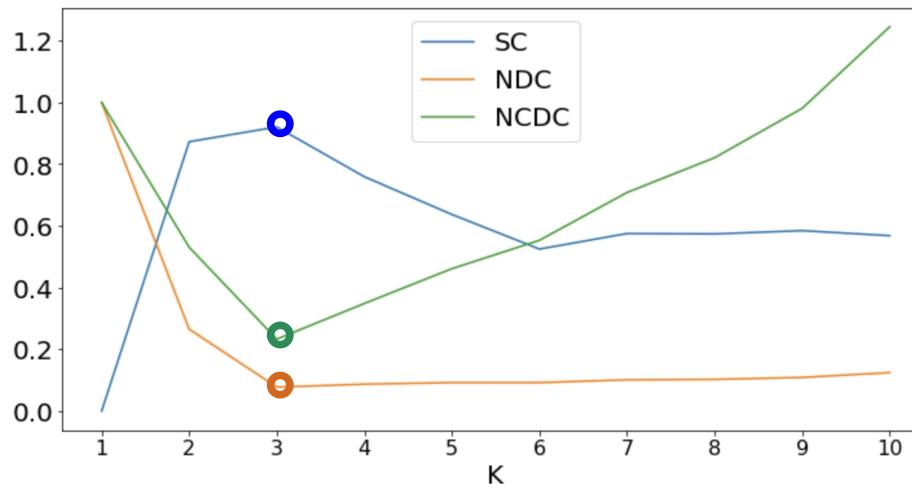
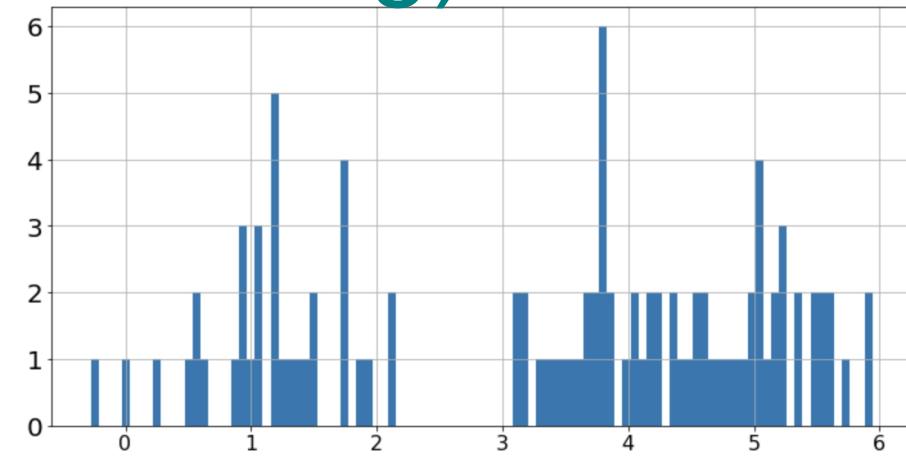
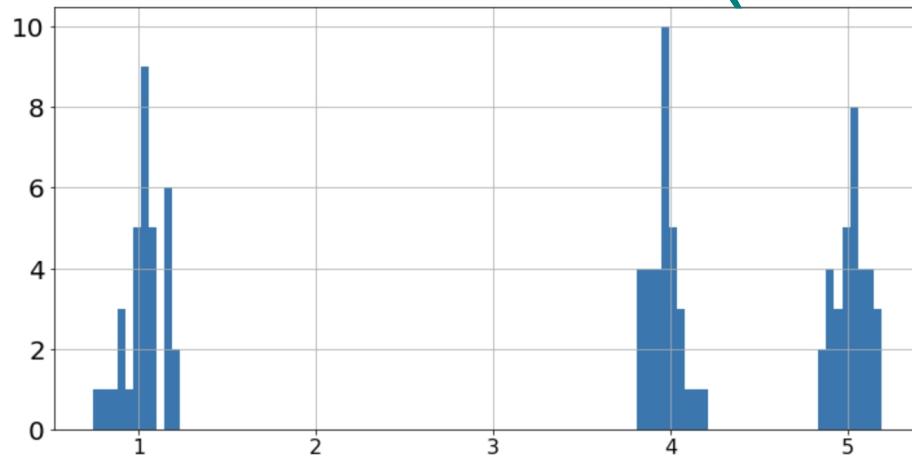
<https://ieeexplore.ieee.org/document/7361868>
<https://github.com/aigents/aigents-java>

<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/>

Unsupervised Clustering

No magic K values and thresholds
are known!!!

Quantification (1-D Clustering) Measures



Quantification for Symbolization

Resume:

"K-means" works, with evaluation of optimal number of clusters based on either of the following:

1. Maximizing "Silhouette Coefficient" (SC), which appears more human-intuitive but does not work for K=1

[https://en.wikipedia.org/wiki/Silhouette_\(clustering\)](https://en.wikipedia.org/wiki/Silhouette_(clustering))

<https://towardsdatascience.com/silhouette-coefficient-validating-clustering-techniques-e976bb81d10c>

2. Minimizing "Normalized Centroid Distance" (NCD) - based on "minimum description length" idea, works for K=1, does not align with human "reductionist" intuition for diverse distributions (tends to create more clusters than needed)

https://www.researchgate.net/publication/221020638_Cluster_Validity_Measures_Based_on_the_Minimum_Description_Length_Principle

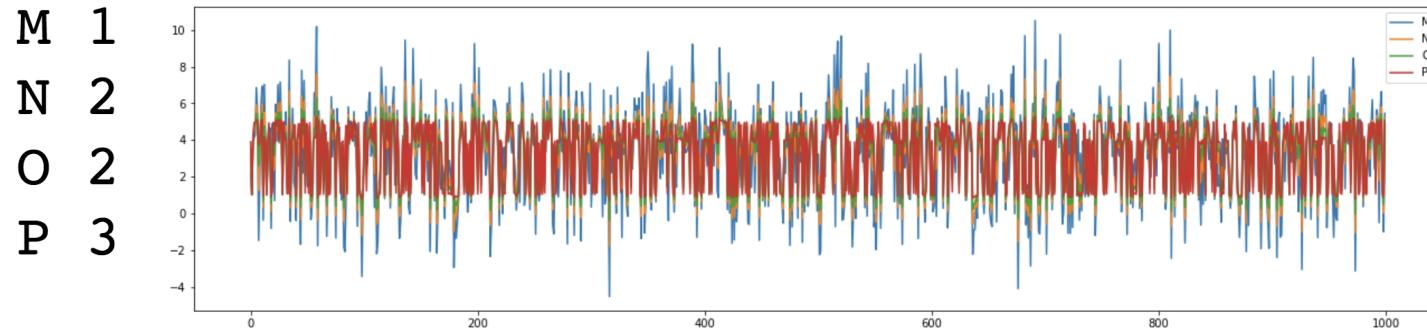
3. Minimizing "Normalized Centroid Distance times Centroids" (NCDC) - extends NCD multiplying it by number of clusters to penalize creation of too many clusters, works for K=1, more human-intuitive than NCD but less human-intuitive than SC

4. Using SC+ (maximize SC if it is above threshold 0.65 or minimize NCDC otherwise) - seems generally optimal from human intuition perspective

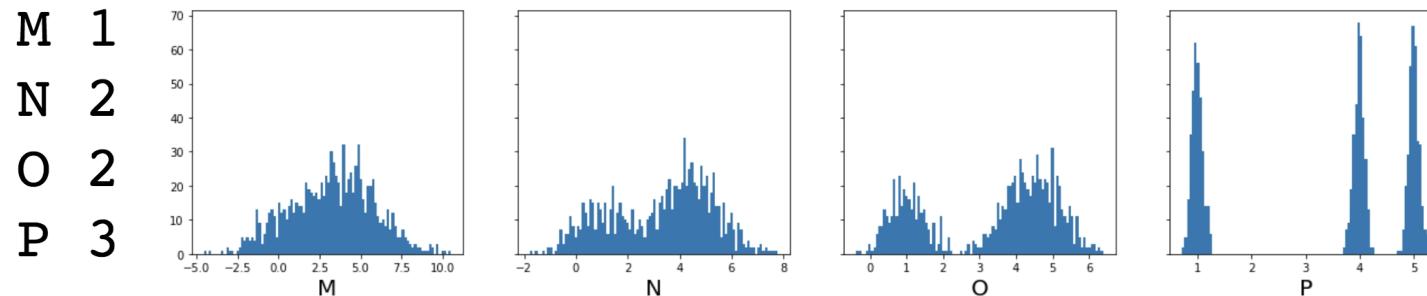
https://github.com/aigents/pygents/blob/main/notebooks/cluster/distribution_modes.ipynb

Quantification – Example 1

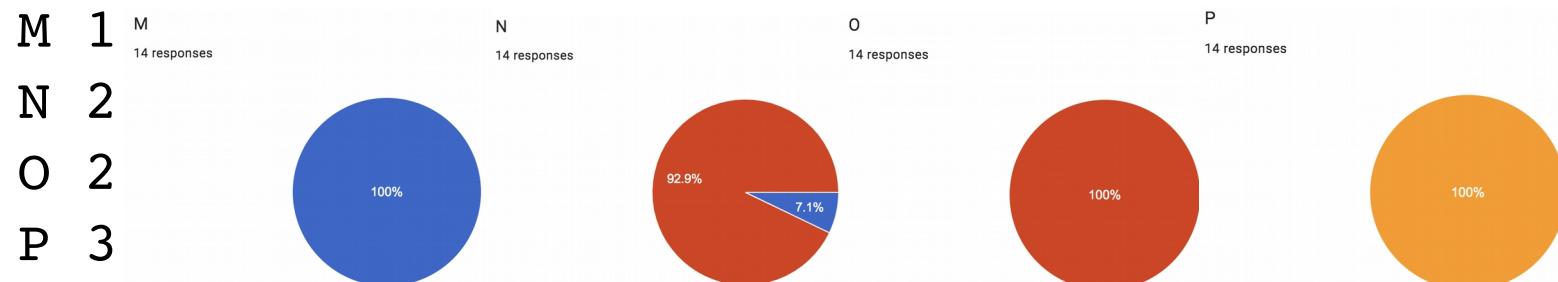
NCDC



SC+



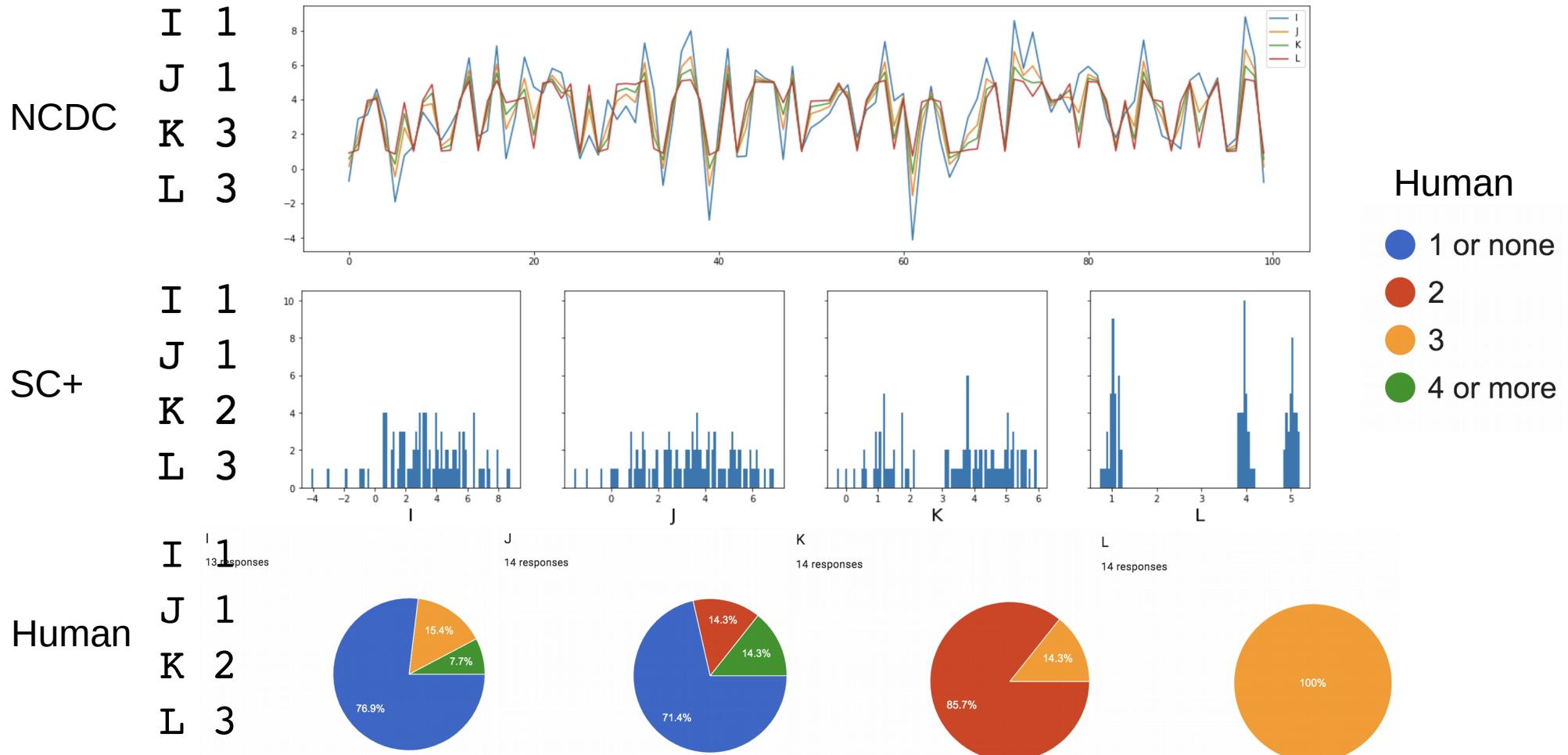
Human



Human

- 1 or none
- 2
- 3
- 4 or more

Quantification – Example 2



Quantification: Human vs. Machine

Evaluate with "Fleiss' kappa" (FK) and "Krippendorff's alpha" (KA)

https://en.wikipedia.org/wiki/Fleiss%27_kappa

<https://stackoverflow.com/questions/51919897/is-fleiss-kappa-a-reliable-measure-for-interannotator-agreement-the-following-r>

<https://bmcmedresmethodol.biomedcentral.com/articles/10.1186/s12874-016-0200-9>

https://www.statsmodels.org/dev/generated/statsmodels.stats.inter_rater.fleiss_kappa.html

NCDC vs. SC+: 0.55, 0.56 (Moderate agreement)

Humans vs. humans: 0.59, 0.59 (Moderate agreement)

NCDC vs. humans: 0.47, 0.48 (Moderate agreement)

SC+ vs. humans: **0.92, 0.92** (Almost perfect agreement)

Unsupervised Segmentation

No stop/start/break tokens, lexicons and
rules are known!!!

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

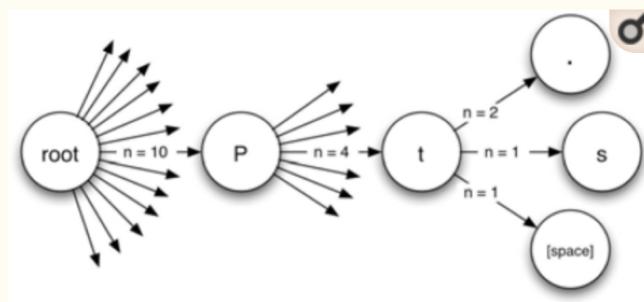


Figure 1

Trie data structure. The probability of observing an ‘s’ given the preceding string “Pt” is $\frac{1}{4}$, or 25%. The freedom following “pt” is 3.

Metrics/Indicators:

Mutual Information¹

Conditional Probability^{1,2}

Transition Freedom^{2,3}

¹ <https://scholarsarchive.byu.edu/cgi/viewcontent.cgi?article=6983&context=etd>

² <https://www.ncbi.nlm.nih.gov/pmc/articles/PMC2655800/>

³ Karl Friston. The free-energy principle: a unified brain theory?
<https://www.nature.com/articles/nrn2787>

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) → Is the correct answer ranked higher?
P(The roses in the vase by the door is) → $P(\dots\text{are}) > P(\dots\text{is})$?

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.

is/are	
The roses <u>?</u>	Simple: no attractors
The roses in the <u>vase</u> <u>?</u>	Harder: 1 attractor
The roses in the <u>vase</u> by the <u>door</u> <u>?</u>	Harder: 2 attractors

Attractors: nouns with different number than 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://arxiv.org/abs/2205.11443>

<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 ($dvp-/dvp+$) from mean

Derivative ($dp-/dp+$) and “Peak”

Transition Freedom ($f-/f+$)

Deviation ($dvf-/dvf+$) from mean

Derivative ($df-/df+$) and “Peak”

Hyper-parameters:

Combination of Ngram ranks N ([1],[2],[3],[1,2],[1,2,3],...)

Threshold for model compression

Threshold for segmentation

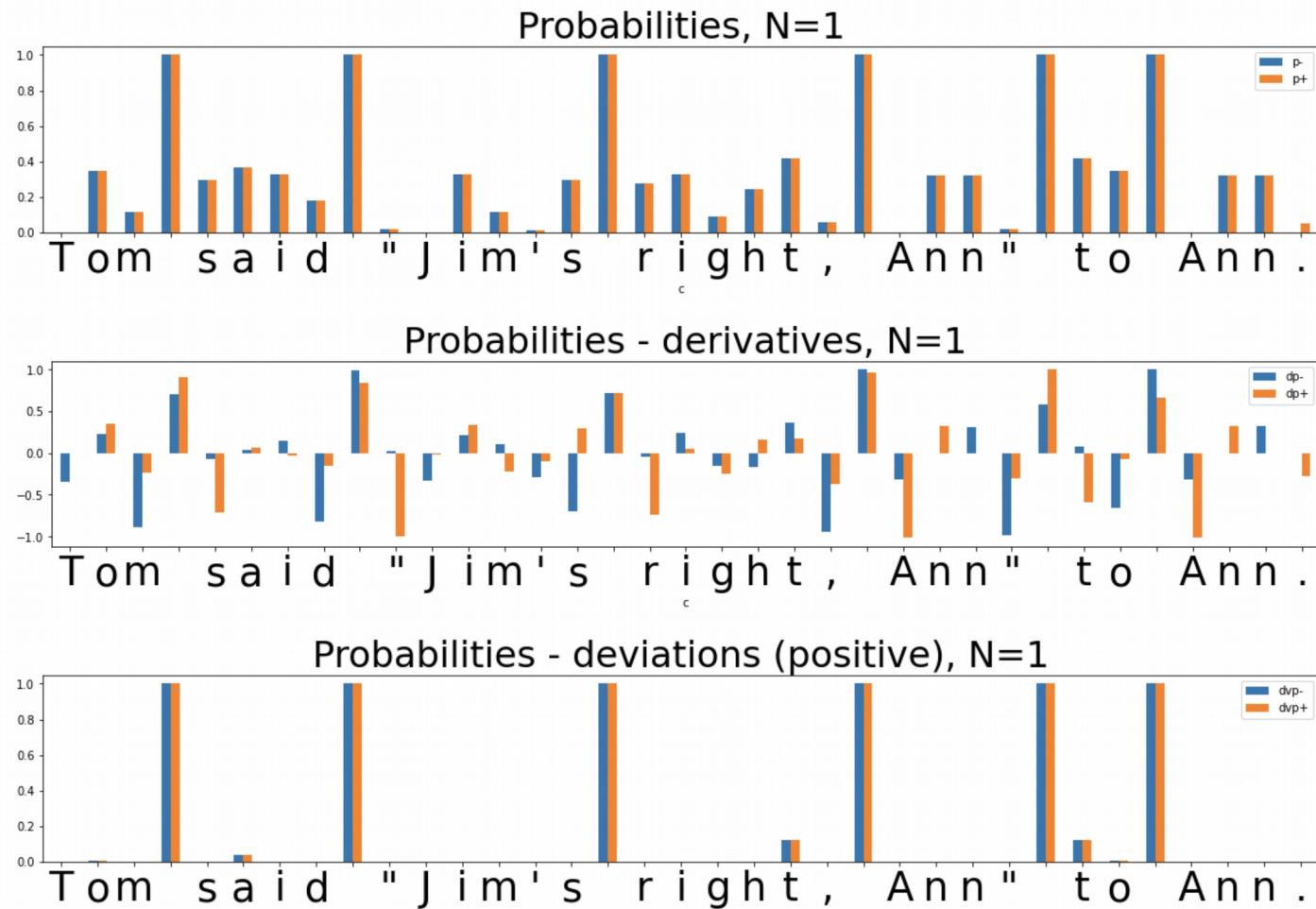
Evaluations:

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

Precision on set of tokens found comparing to reference lexicons

Unsupervised Text Segmentation (Tokenization)

Metrics/Indicators:
Ngram (Character)
Probability



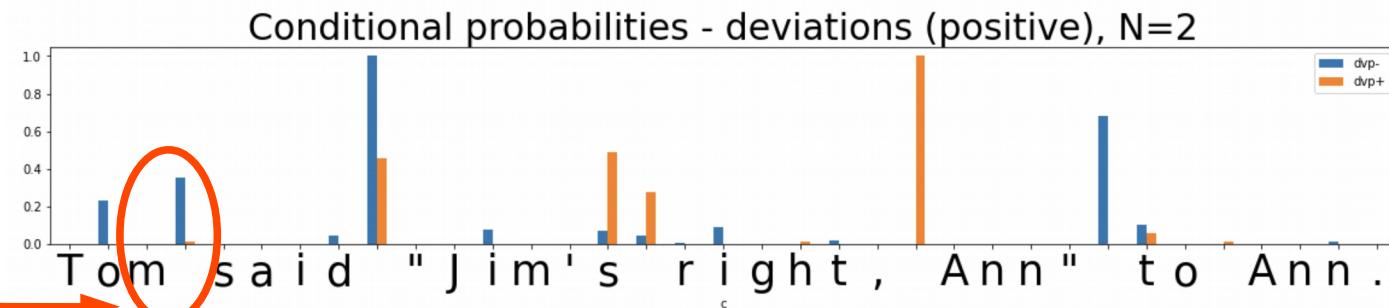
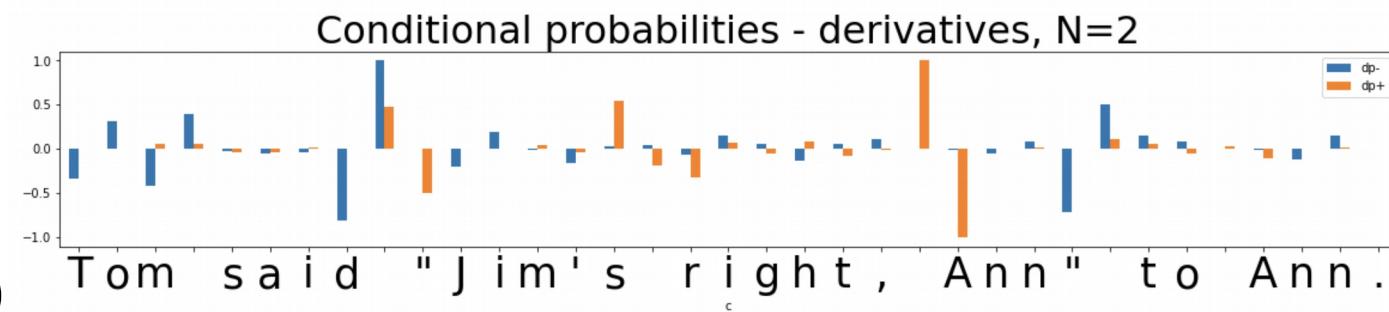
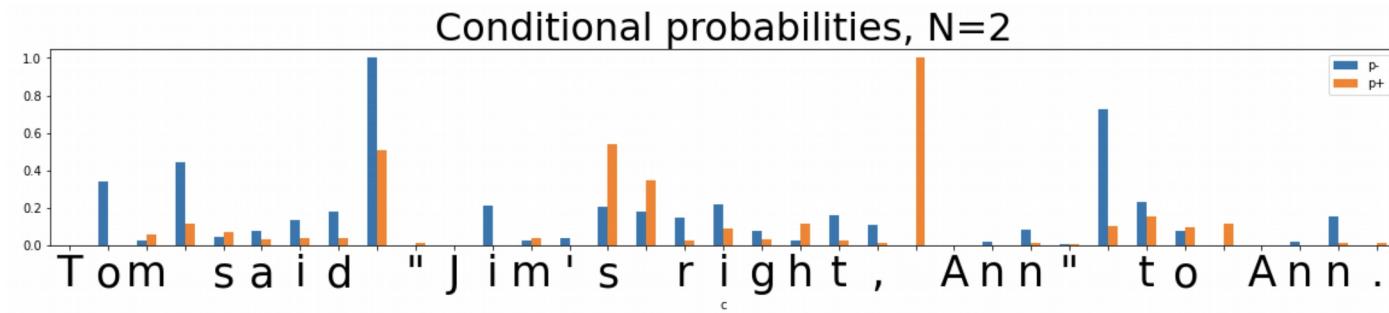
Unsupervised Text Segmentation (Tokenization)

Metrics/Indicators:

Ngram (Character)
Conditional
Probability
(of Transition)

$P(\text{Ngram}_{n+1})/P(\text{Ngram}_n)$

$P("m")/P(m")$



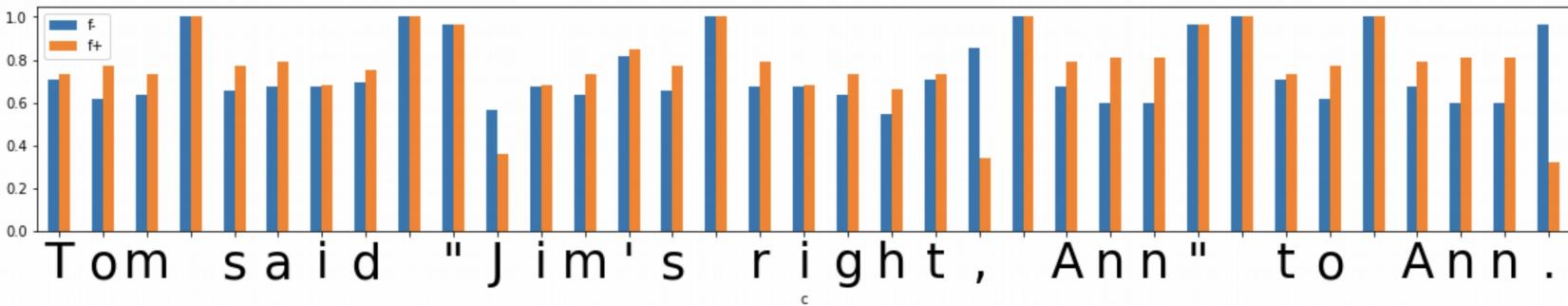
Unsupervised Text Segmentation (Tokenization)

```
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
```

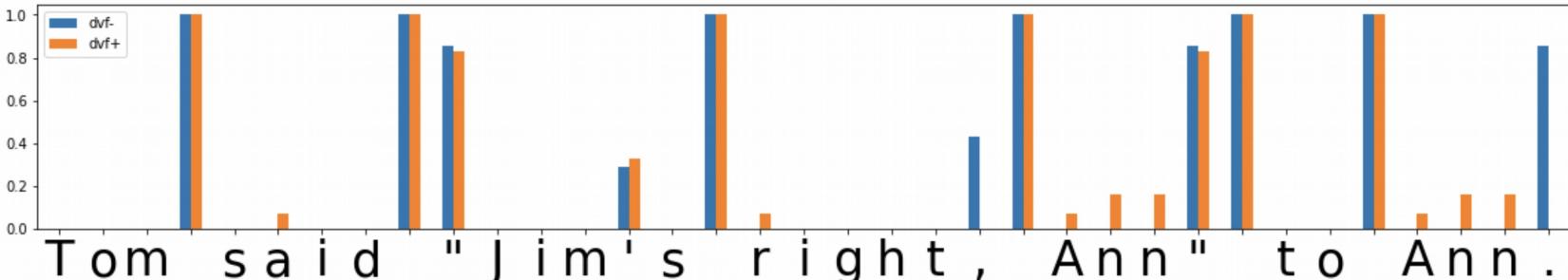
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['Tom', ' ', 'said', ' ', "'", "Jim's", ' ', 'right', ' ', ' ', 'Ann', ' ', ' ', 'to', ' ', ' ', 'Ann', '.']
['Tom', ' ', 'said', ' ', "'", "Jim's", ' ', 'right', ' ', ' ', 'Ann', ' ', ' ', 'to', ' ', ' ', 'Ann', '.']
1.0
```

Metrics/ Indicators:

Transition
Freedom
(Freedom of
Transition)



Transition
Freedom
Deviation



Unsupervised Text Segmentation (Tokenization)

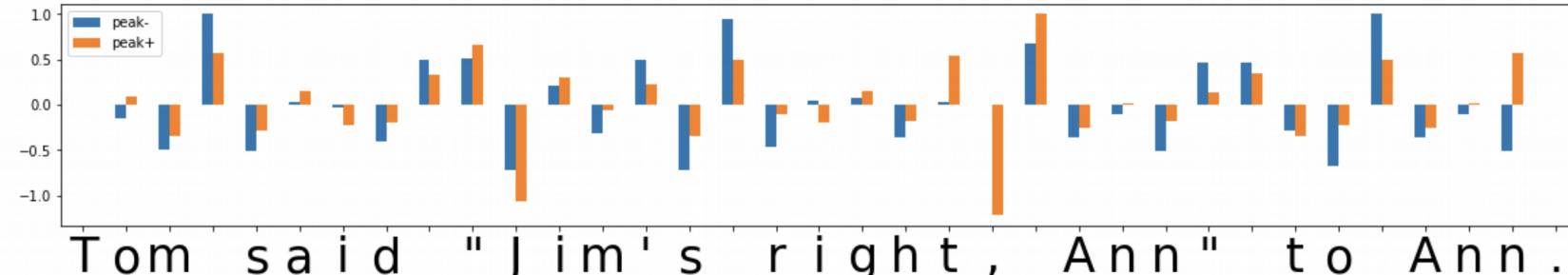
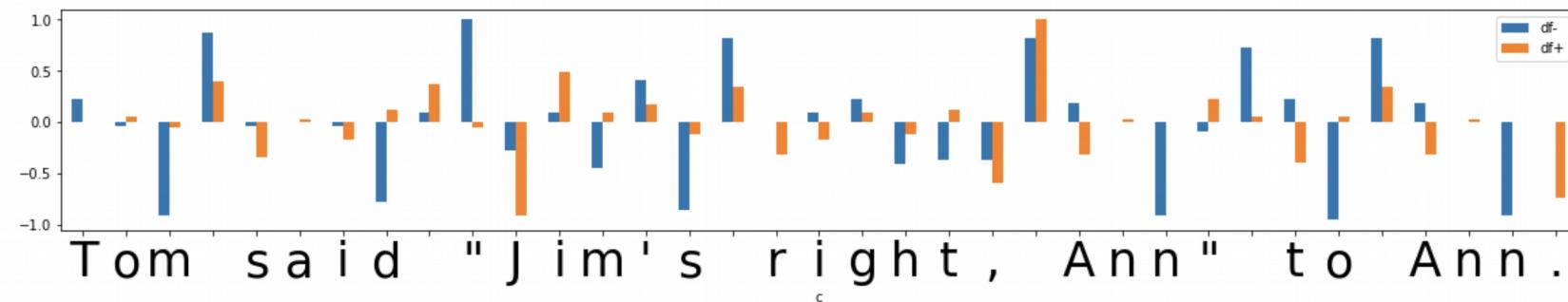
Metrics/ Indicators:

Transition
Freedom
(Freedom of
Transition)
Derivative

Transition
Freedom
“Peak”)

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

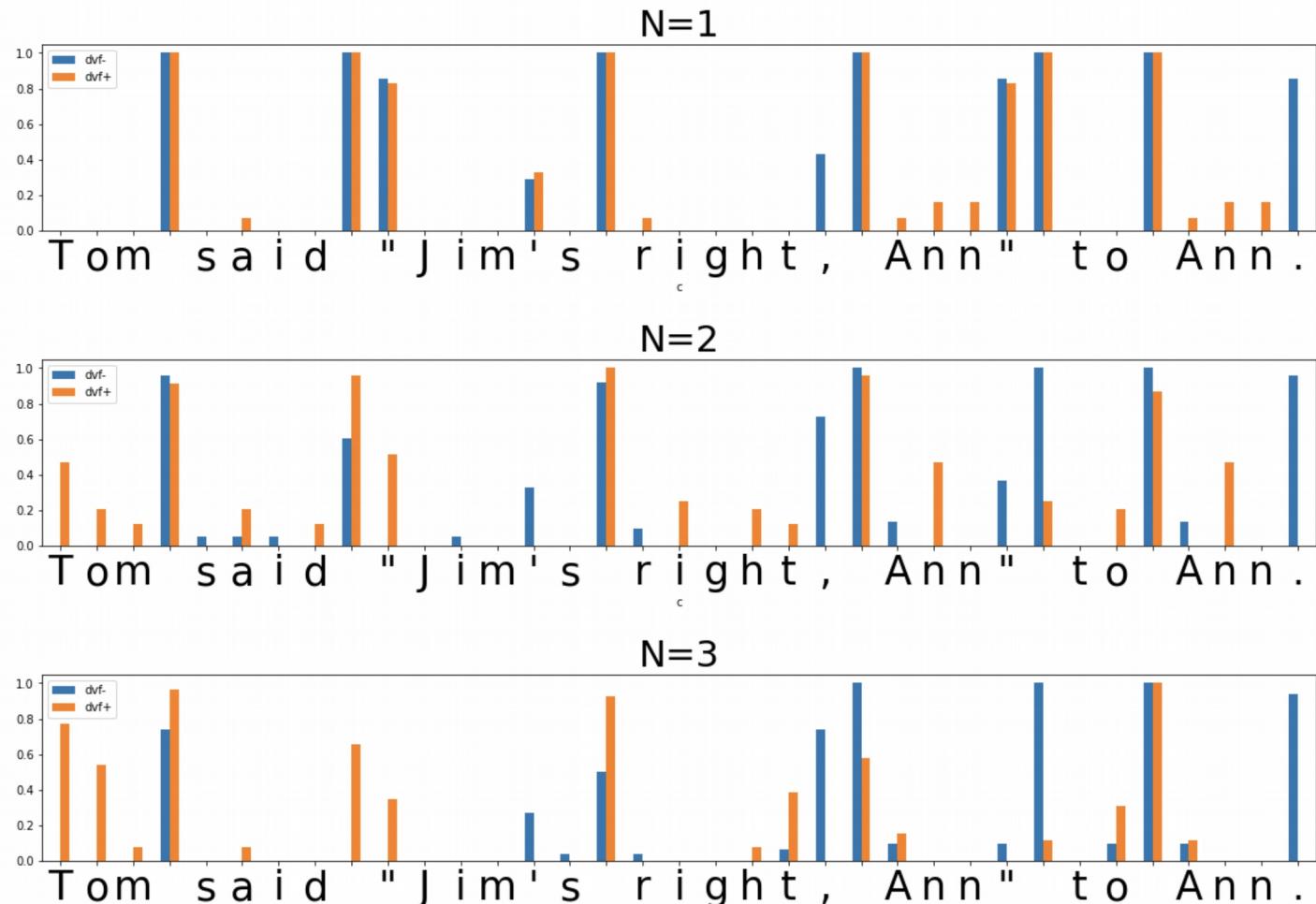


Unsupervised Text Segmentation (Tokenization)

Metrics/
Indicators:

Transition
Freedom
Deviation

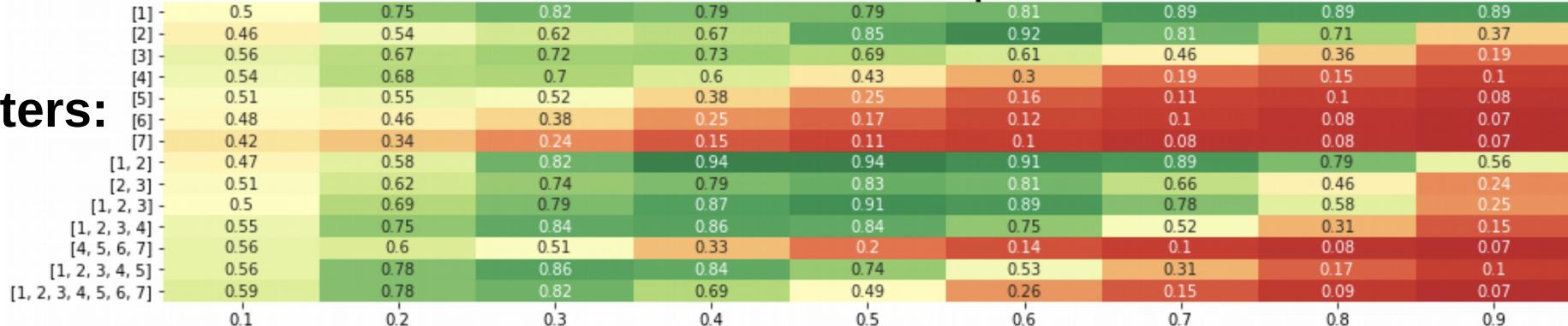
(varying “N”
of N-gram)



Unsupervised Text Segmentation (Tokenization)

English

F1 - Brown ddf- & ddf+ filter=0 parameters=10967135



Hyper-Parameters:

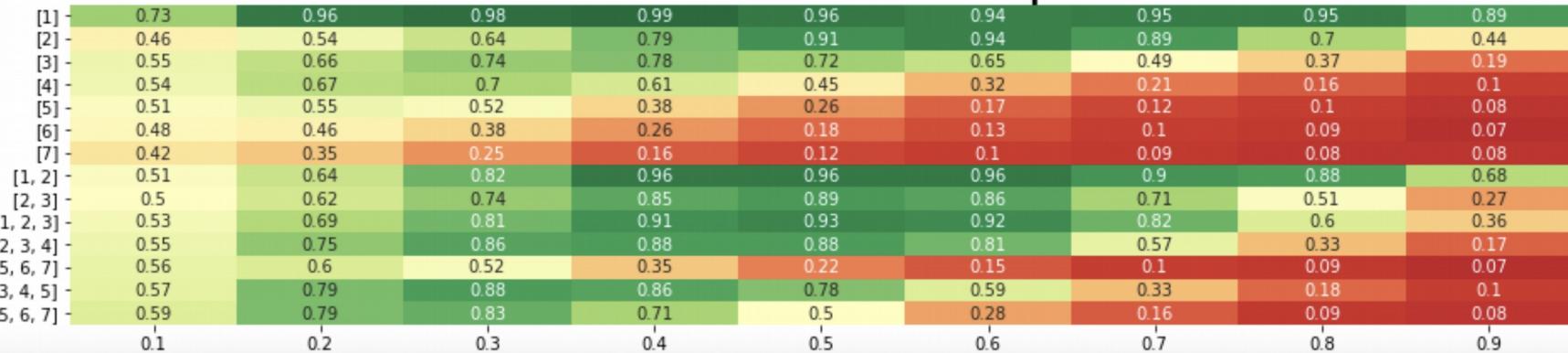
Metric:
Transition
Freedom

Threshold
for model
compression

Combination
of Ngram N-s

Threshold for
segmentation

F1 - Brown ddf- & ddf+ filter=0.0001 parameters=8643703



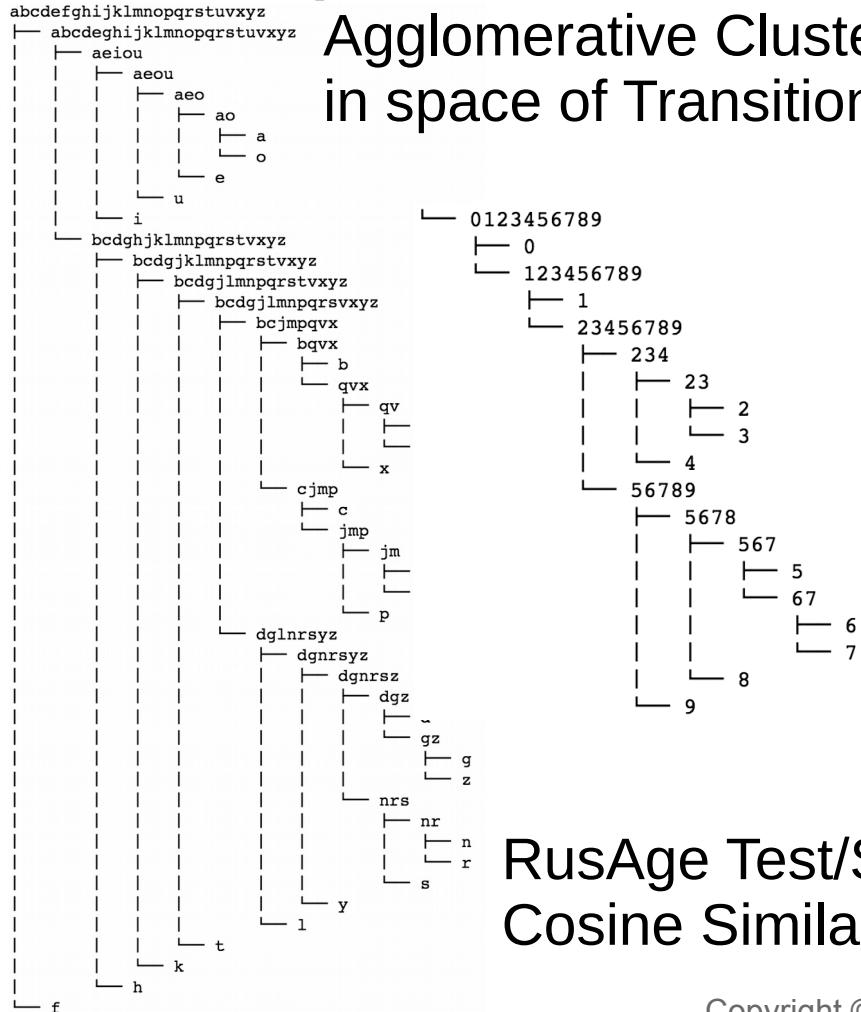
Results – Freedom-based Tokenization against Lexicon

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	-

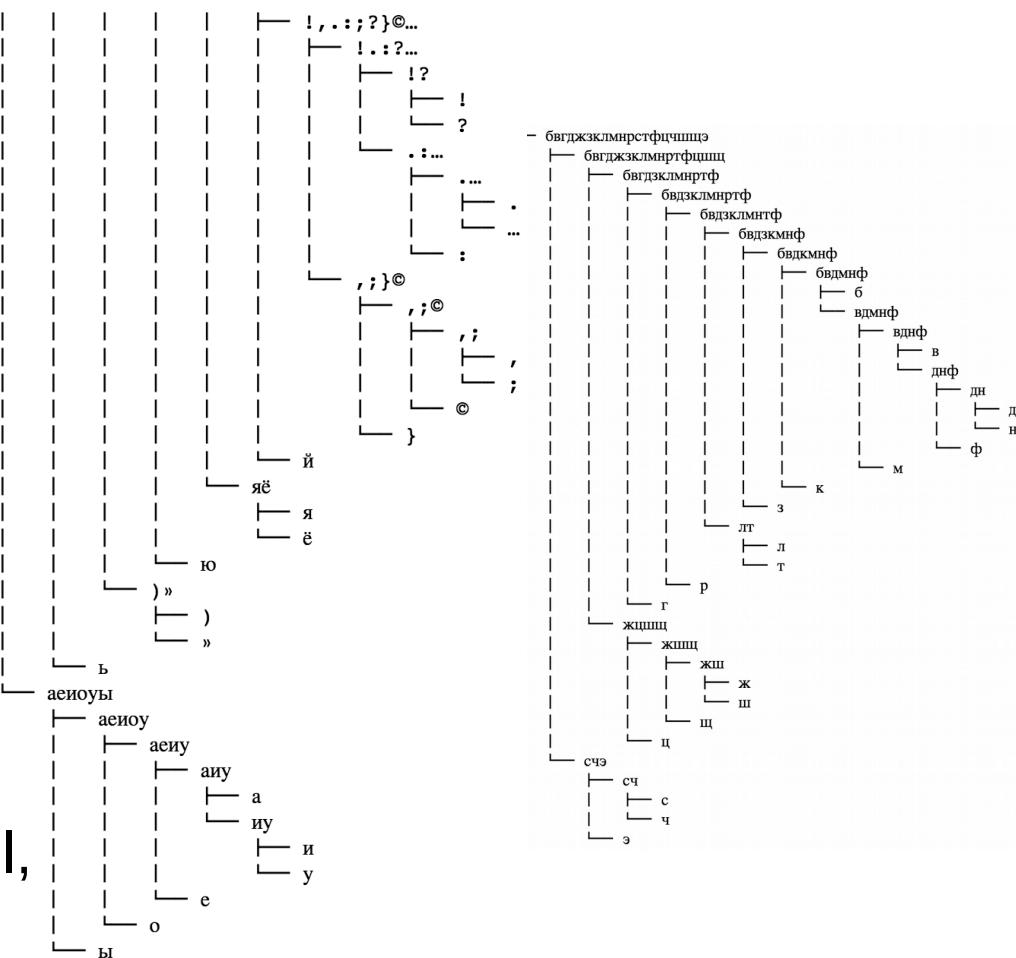
Lexicon-based Tokenization - greedy/beam search on word length (optimal) or frequency

Unsupervised Character Category Learning

Agglomerative Clustering in space of Transitions



RusAge Test/Small, Cosine Similarity



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.

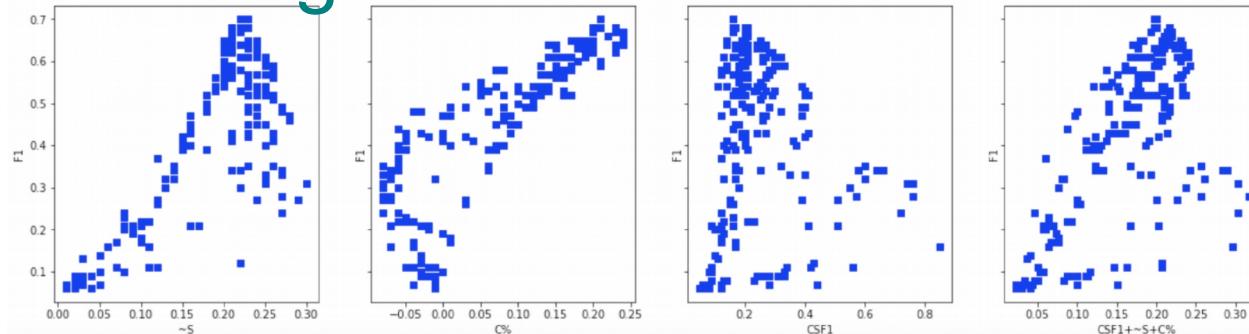
Applications for other Experiential Learning environments, including the ones with delayed/sparse feedback.

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

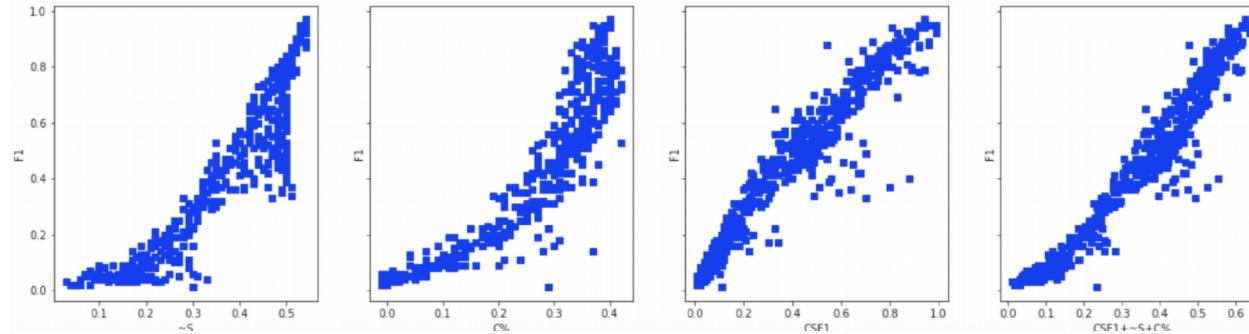
<https://arxiv.org/abs/2205.11443>
<https://github.com/aigents/pygents>

Something about Human Intuition?

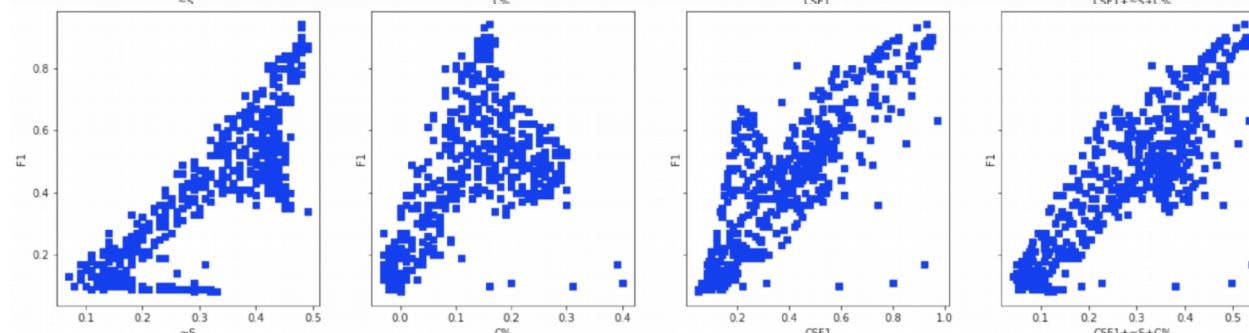
Language 1



Language 2

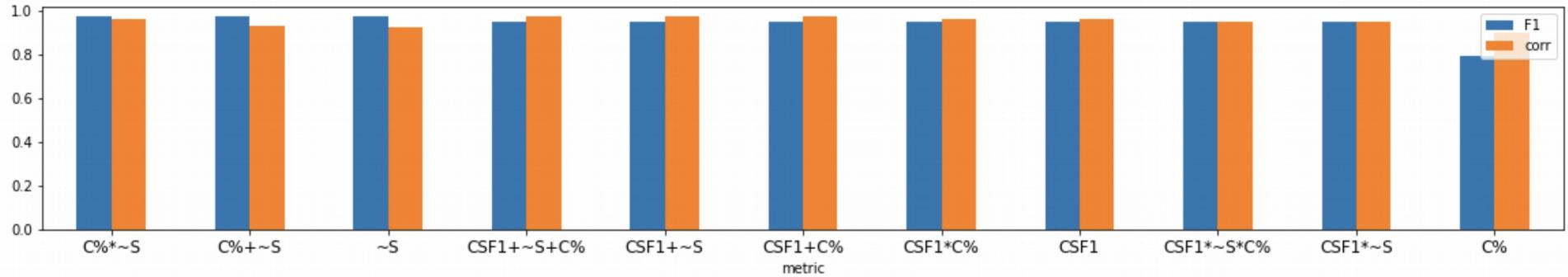


Language 3

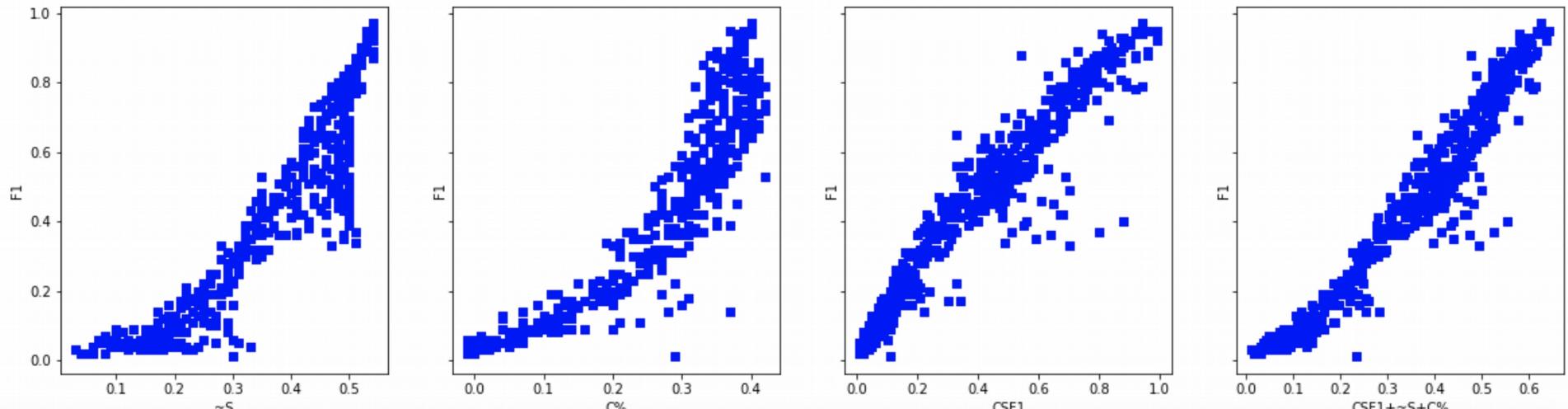


Self-tuning Hyperparameters – English (TF variance)

Test 1000

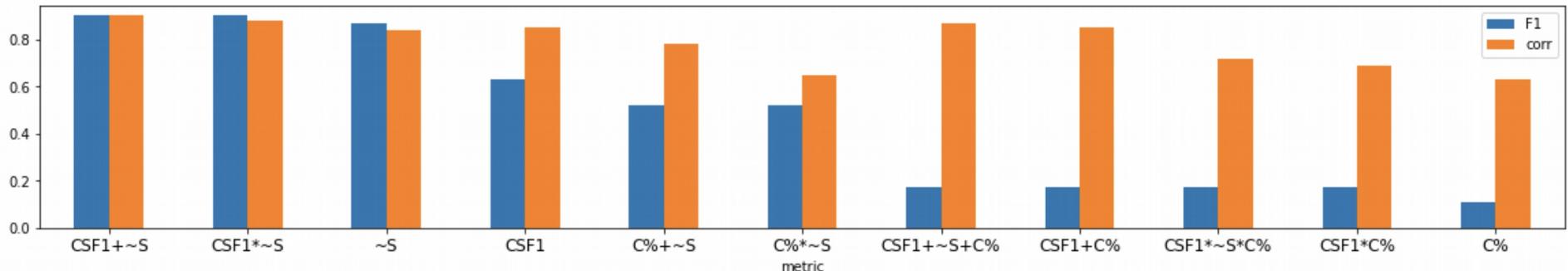


F1 as function of $\sim S$, C% and CSF1 used for hyper-parameter selection

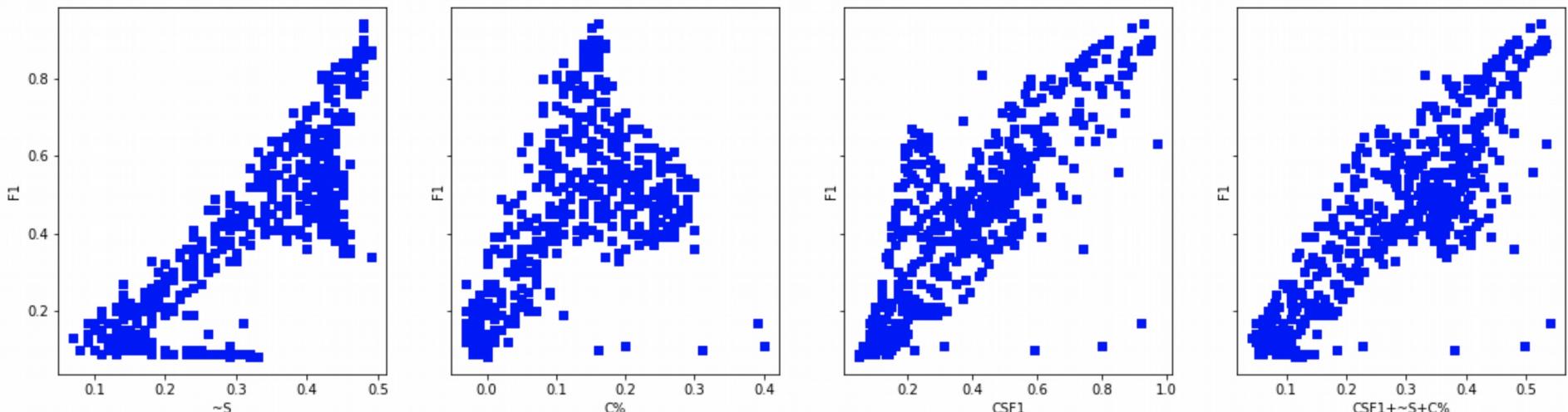


Self-tuning Hyperparameters – Russian (TF variance)

Test 1000

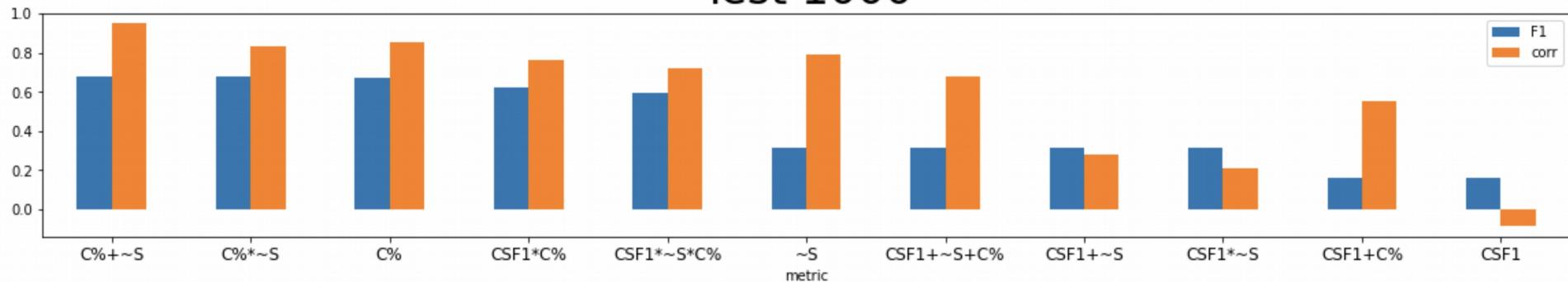


F1 as function of $\sim S$, $C\%$ and $CSF1$ used for hyper-parameter selection

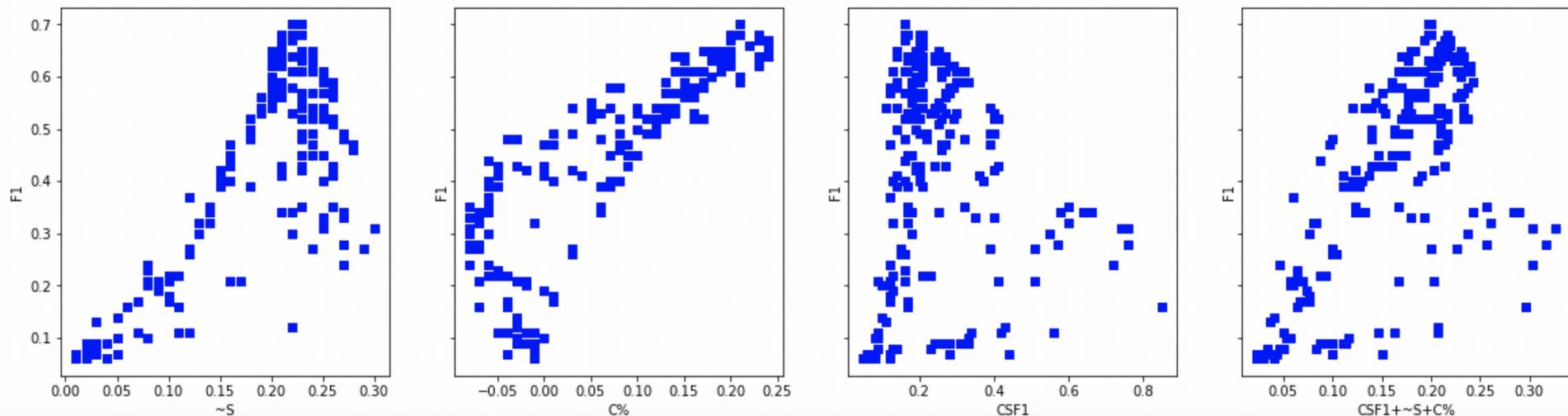


Self-tuning Hyperparameters – Chinese (TF “peak”)

Test 1000



F1 as function of $\sim S$, C% and CSF1 used for hyper-parameter selection



Something about Human Intuition!

Screen Shot 2022-06-16 at 11.08.54.png
247.8 KB

OPEN WITH

Language 1 11:22 ✓

Screen Shot 2022-06-16 at 11.09.45.png
256.8 KB

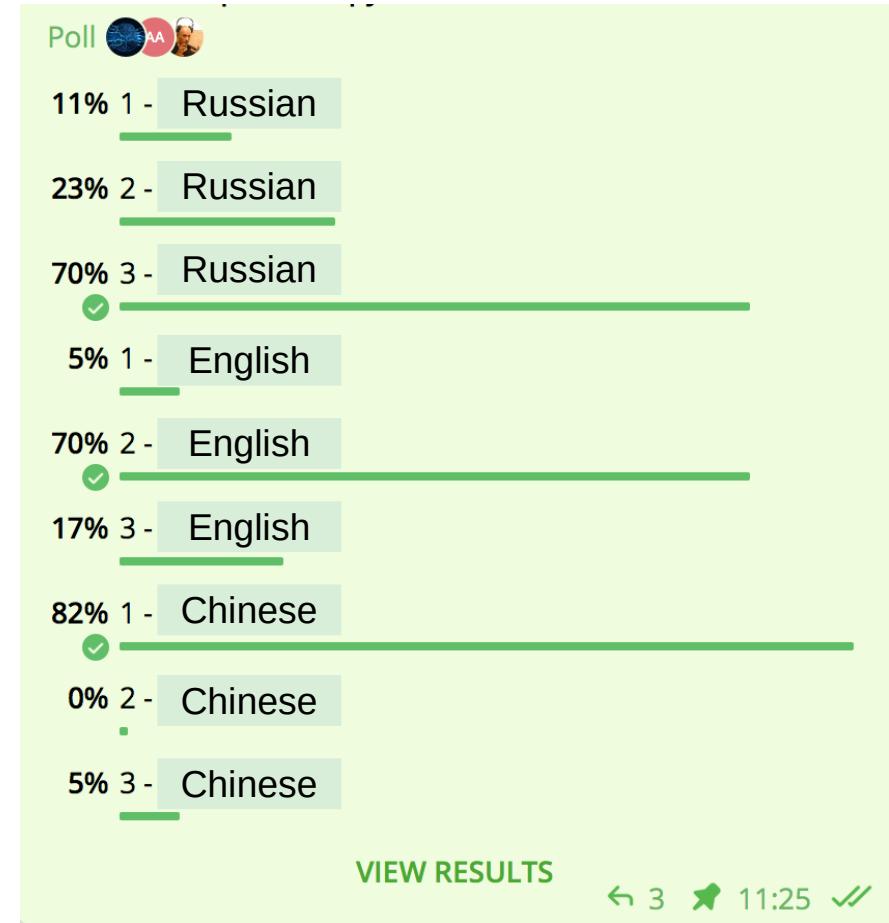
OPEN WITH

Language 2 11:23 ✓

Screen Shot 2022-06-16 at 11.09.59.png
276.4 KB

OPEN WITH

Language 3 11:23 ✓



Thank You and Welcome!

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