Experiential Learning from Sequential Data

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*THE REAL SCIENCE

SingularityNET

AGI IN RUSSIAN

https://agirussia.org

AIGENTS

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Motivation

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

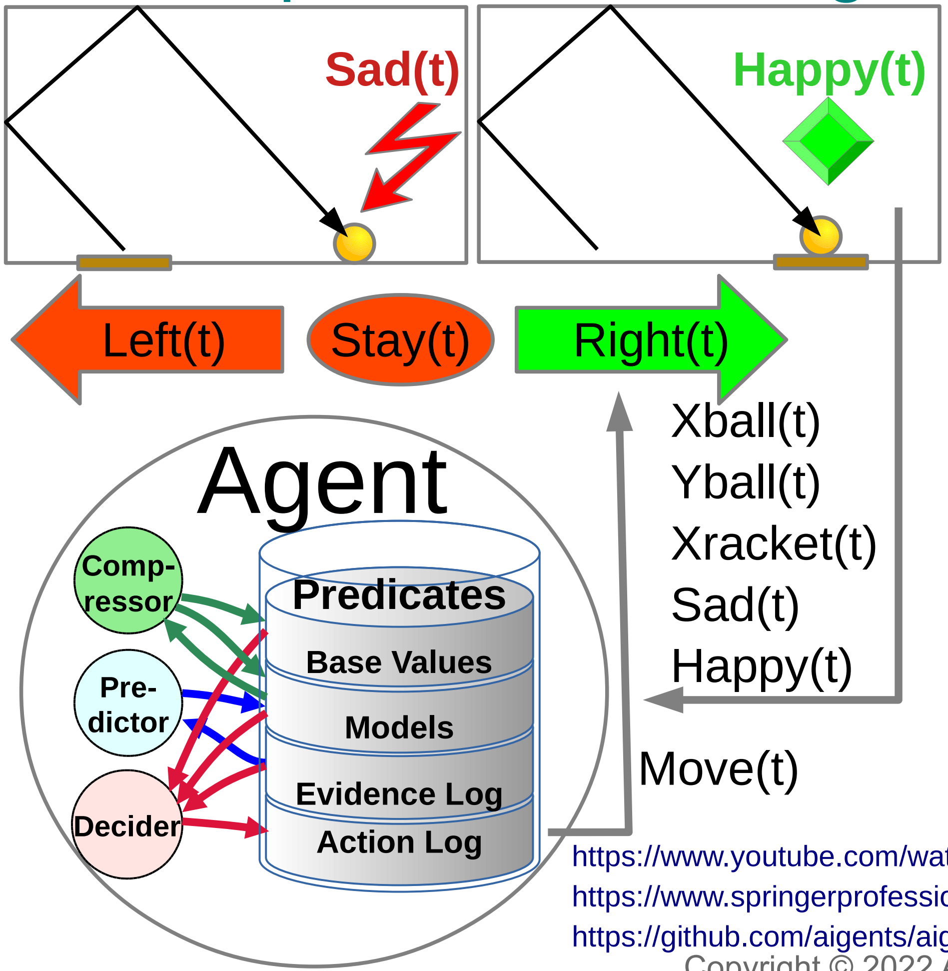
Discovering NLP patterns such as words and punctuation for further unsupervised language learning

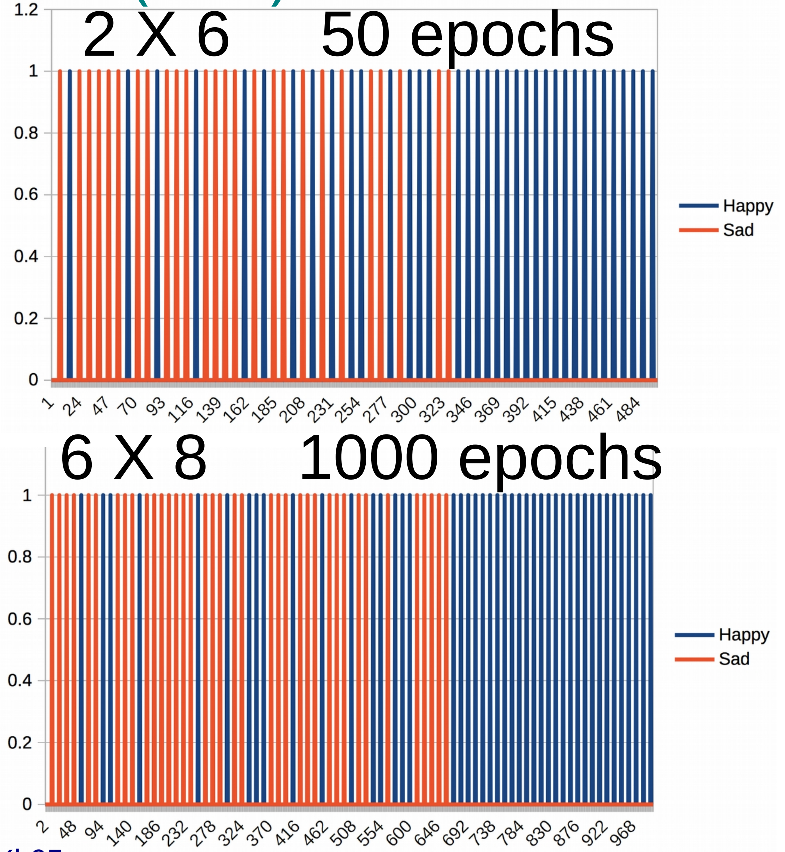
https://arxiv.org/abs/2205.11443

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

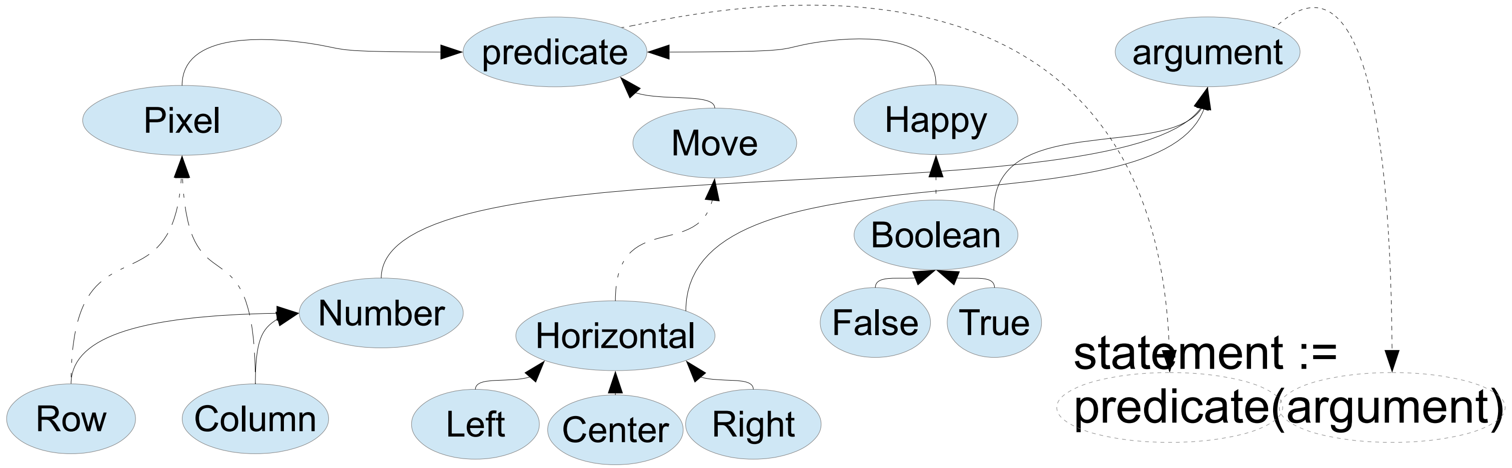
Identifying successful/unsuccessful sequential experiences for experiential learning with global (self)reinforcement

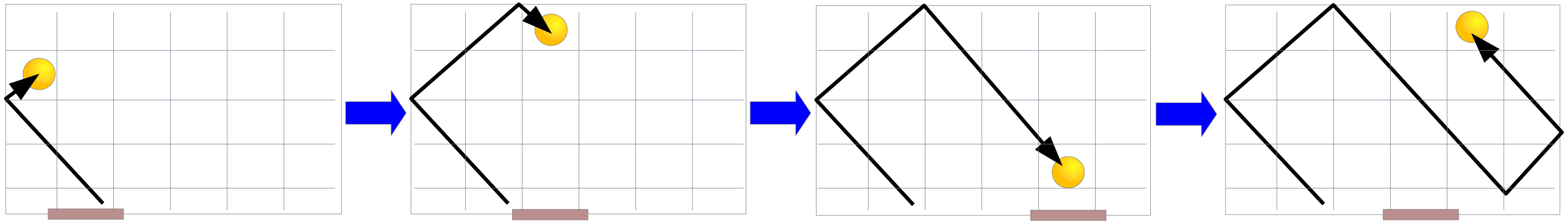




https://www.youtube.com/watch?v=2LPLhJKh95g
https://www.springerprofessional.de/neuro-symbolic-architecture-for-experiential-learning-in-discret/20008336
https://github.com/aigents/aigents-java/tree/master/src/main/java/net/webstructor/agi

Ontology and Grammar ("Discrete")





Pixel(1,0)
Pixel(4,1)
Happy(False)
=>
Move(Left)

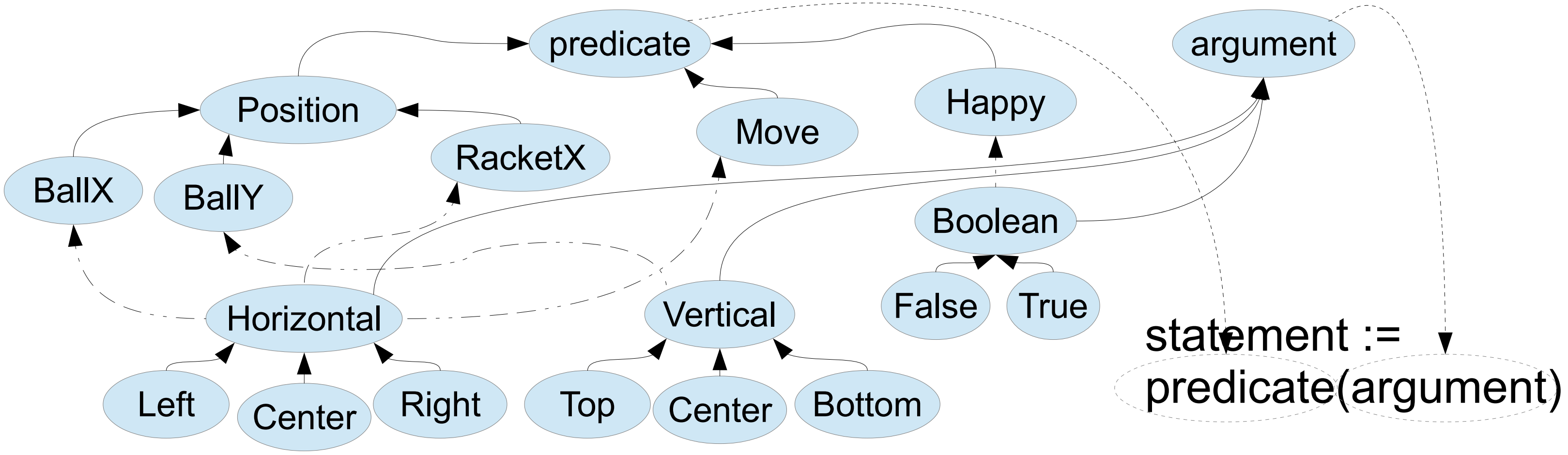
Pixel(0,2)
Pixel(4,2)
Happy(False)
=>
Move(Right)

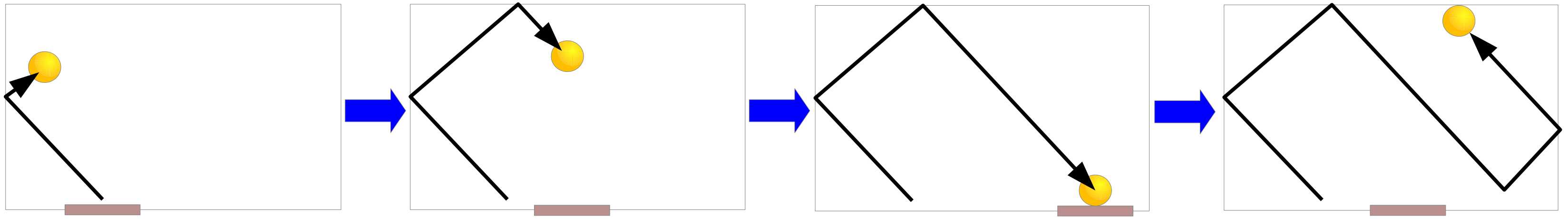
Pixel(3,4)
Pixel(4,4)
Happy(False)
=>
Move(Left)

Pixel(0,4)
Pixel(4,3)
Happy(True)
=>
Move(Left)

Global Feedback

Ontology and Grammar (“Functional”)

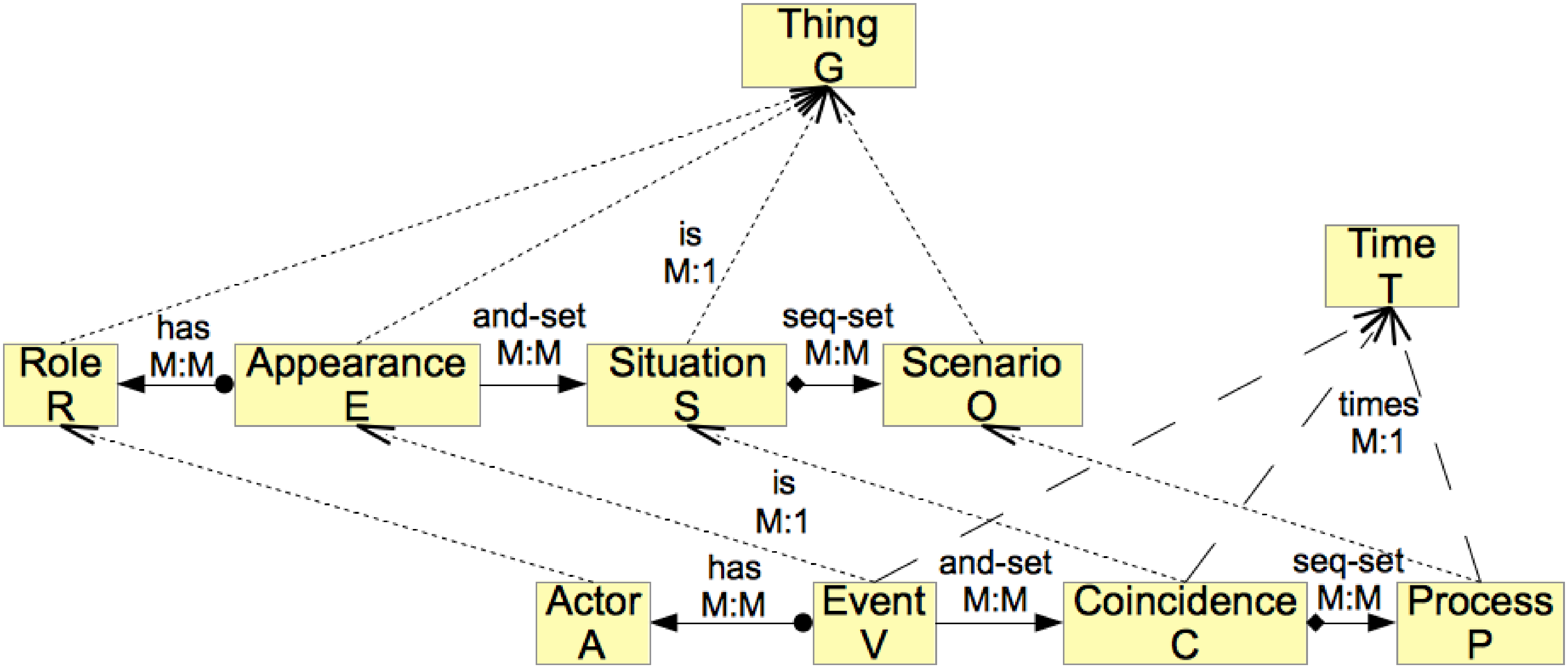




BallY(Top) BallX(Left) RacketX(Left) Happy(False) => **Move(Left)**	BallY(Top) BallX(Center) RacketX(Center) Happy(False) => **Move(Right)**	BallY(Bottom) BallX(Right) RacketX(Right) Happy(False) => **Move(Right)**	BallY(Bottom) BallX(Right) RacketX(Right) **Happy(True)** => **Move(Left)**

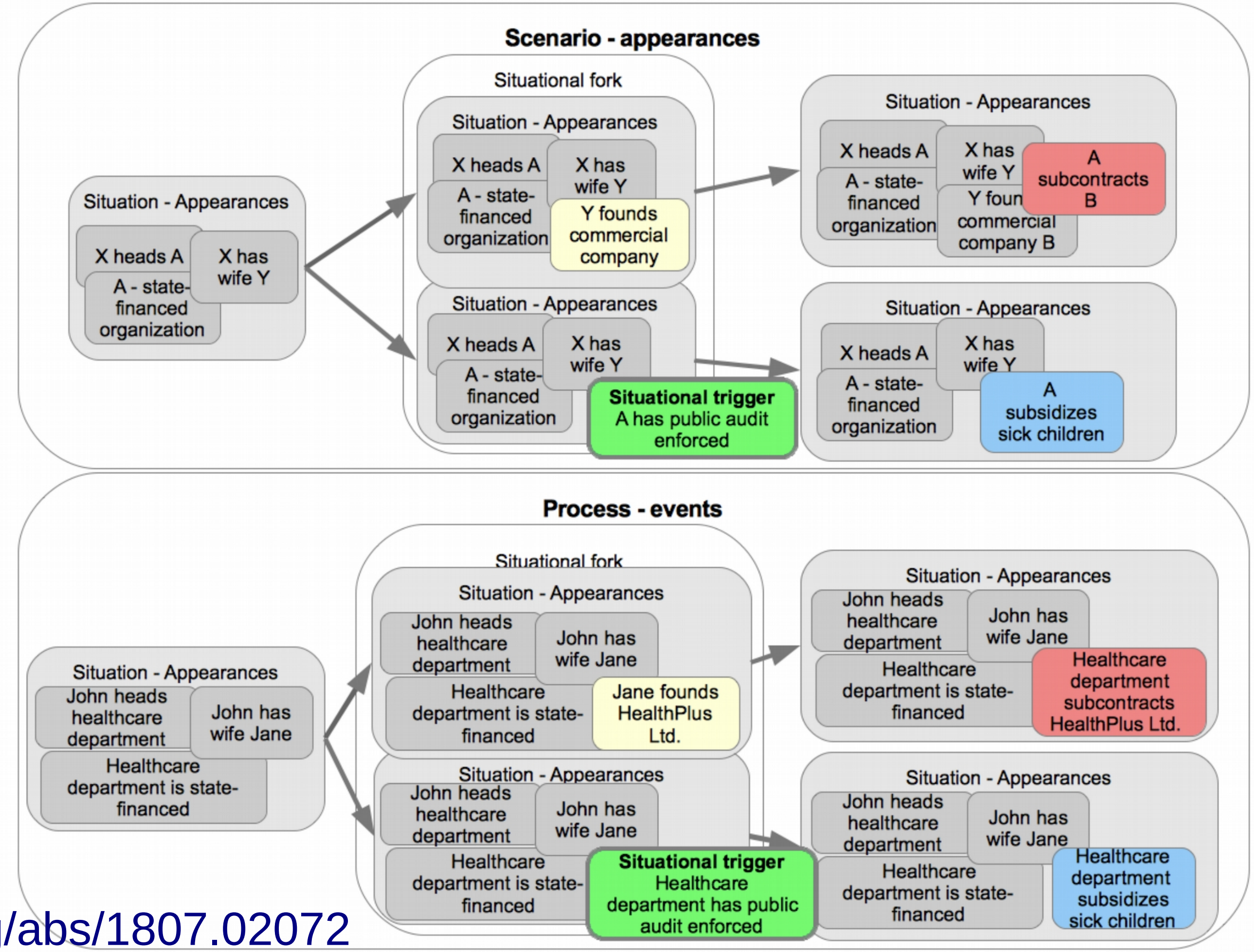
Global Feedback

Foundation (Generic) Activity Ontology



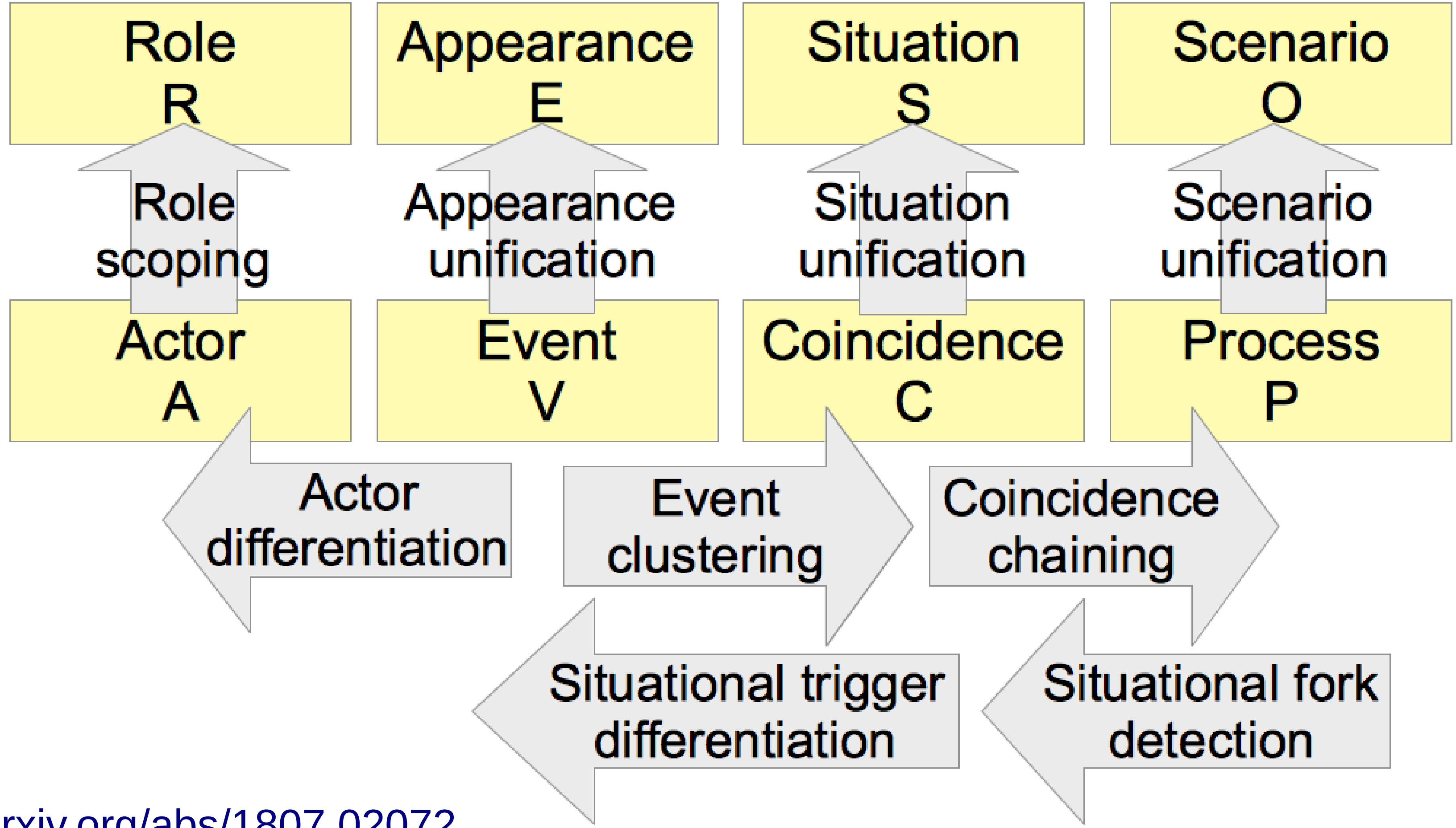
https://arxiv.org/abs/1807.02072

Upper (Domain) Activity Ontology Example



https://arxiv.org/abs/1807.02072

Scenario Mining in Process Data



https://arxiv.org/abs/1807.02072

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: On the top, at the bottom, long, short, skewed, etc.	Object property value: Name "John"	Specific actor: John Doe
Event	Combination of coefficients on spectrogram	Period or stroke composing the letter: .	Object class instance: Name "John", surname "Doe"	Specific event: John Doe cleaning the window on the second floor.
Coincidence	Specific sound	Coincidence: i	Co-occurrence of object of class person properties: "John Doe"	Specific coincidence: Window on the second floor is dirty, John Doe is cleaning it.
Process	Specific spoken word	Specific written word: ping	Specific phrase: "John Doe cleans the window"	Specific process: 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: person's surname	Typical role: Cleaner
Appearance	Spectral cluster on the spectrogram	Element of symbol: .	Class of the variable object: person	Typical appearance: Someone cleaning something
Situation	Sound of speech	Symbol: i	Pattern variable: $subject	Typical situation: Someone is cleaning something which is dirty.
Scenario	Spoken word accordingly to the language model	Written word: ping	Phrase pattern: "$subject cleans $object"	Typical scenario: Something was dirty, someone has cleaned it, it is clean now.

Evgeni Vityaev’s Invariant Structures

Mining temporally invariant structures (“scenarios”) in historical time series data recording financial “processes” with the **Discovery** system.

http://www.math.nsc.ru/AP/ScientificDiscovery/PDF/data_mining_for_financial_applications.pdf

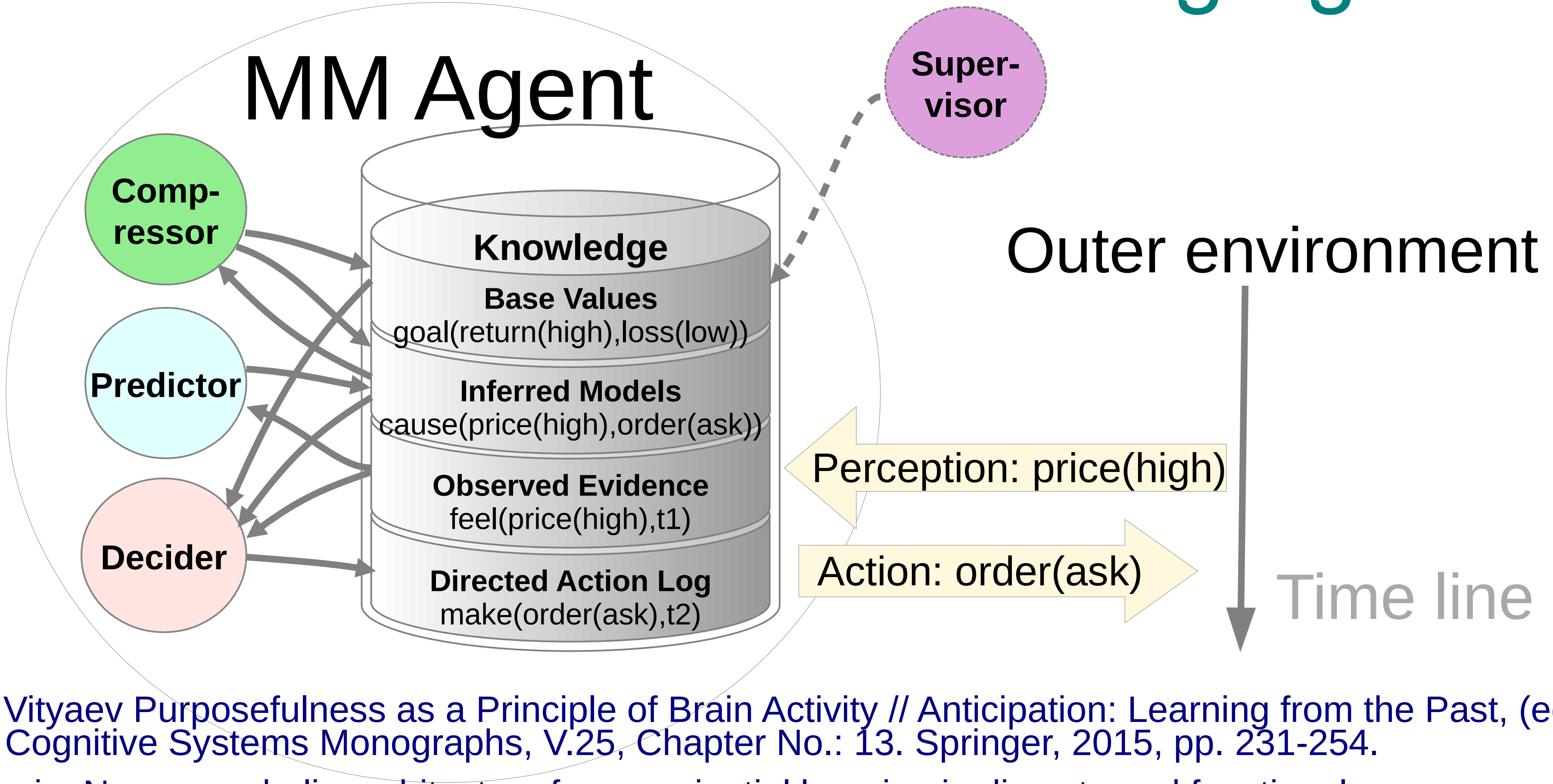
Symbolic Methodology in Numeric Data Mining: Relational Techniques for Financial Applications
Boris Kovalerchuk, Evgenii Vityaev, Husan Yusupov
https://arxiv.org/pdf/cs/0208022.pdf

Brain Principles Programming
Evgenii Vityaev, Anton Kolonin, Andrey Kurpatov, Artem Molchanov
https://arxiv.org/abs/2202.12710

ANNEX IN FINANCIAL FORECASTING

structure1	structure2	structure3	structure4	weekday	week
			forecast for	Friday	forecast week
		forecast for		Thursday	forecast week
			up	Wednesday	forecast week
	forecast for	up		Tuesday	forecast week
forecast for				Monday	forecast week
	up		current day	Friday	current week
				Thursday	current week
up		current day	down	Wednesday	current week
	current day	down		Tuesday	current week
current day			anchor2	Monday	current week
	down	anchor2		Friday	one week ago
	anchor2			Thursday	one week ago
	down anchor1	down		Wednesday	one week ago
down				Tuesday	one week ago
		anchor1		Monday	one week ago
			up	Friday	two weeks ago
				Thursday	two weeks ago
anchor2				Wednesday	two weeks ago
				Tuesday	two weeks ago
up			anchor1	Monday	two weeks ago
anchor1				Friday	three weeks ago
				Thursday	three weeks ago
				Wednesday	three weeks ago
				Tuesday	three weeks ago
				Monday	three weeks ago
training 0.74	training 0.72	training 0.7	training 0.7		
testing 0.78	testing 0.73	testing 0.71	testing 0.82		

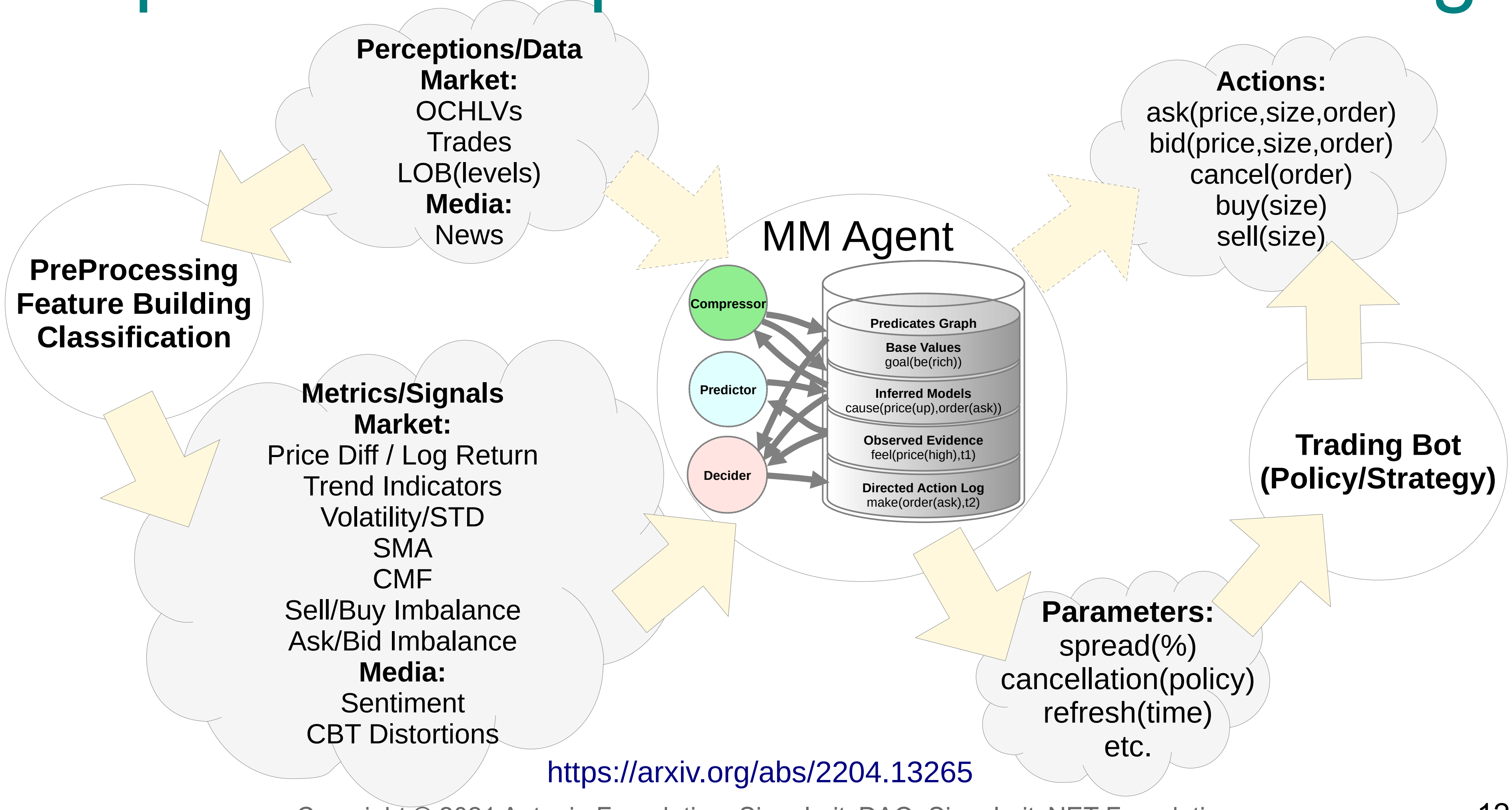
Narrow AGI for Market Making Agent



Evgenii E. Vityaev Purposefulness as a Principle of Brain Activity // Anticipation: Learning from the Past, (ed.) M. Nadin. Cognitive Systems Monographs, V.25, Chapter No.: 13. Springer, 2015, pp. 231-254.

Anton Kolonin: Neuro-symbolic architecture for experiential learning in discrete and functional environments // AGI-2021 Conference Proceedings, 2021

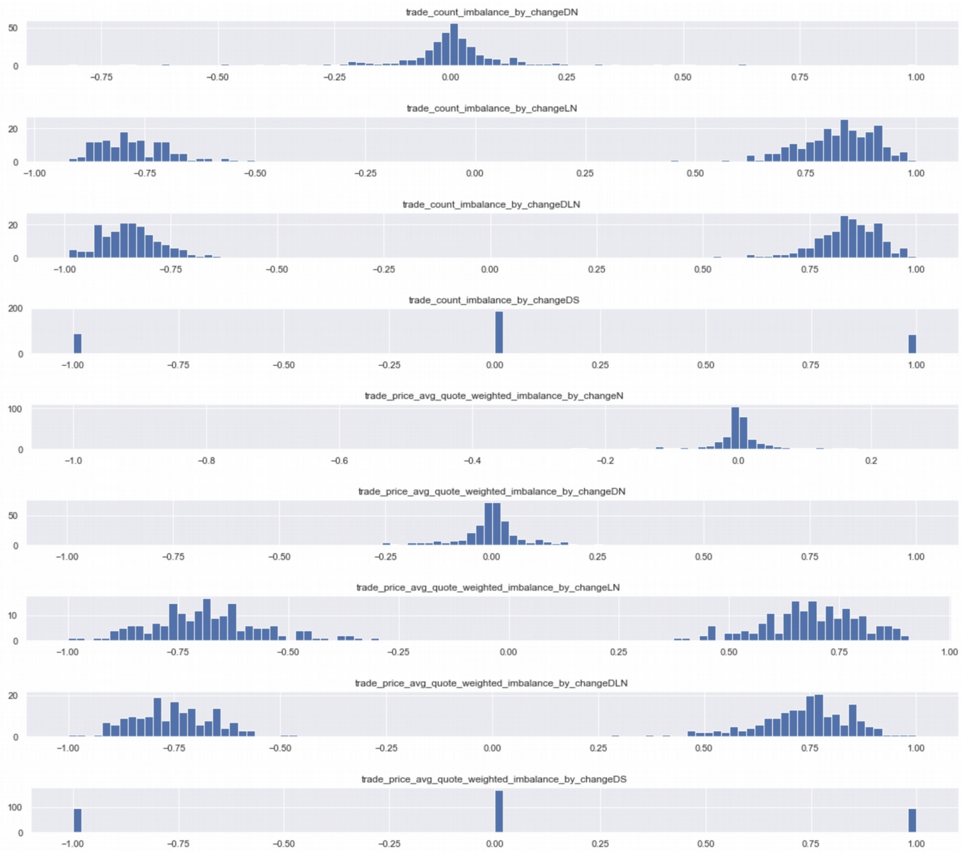
Operational Space for Market Making



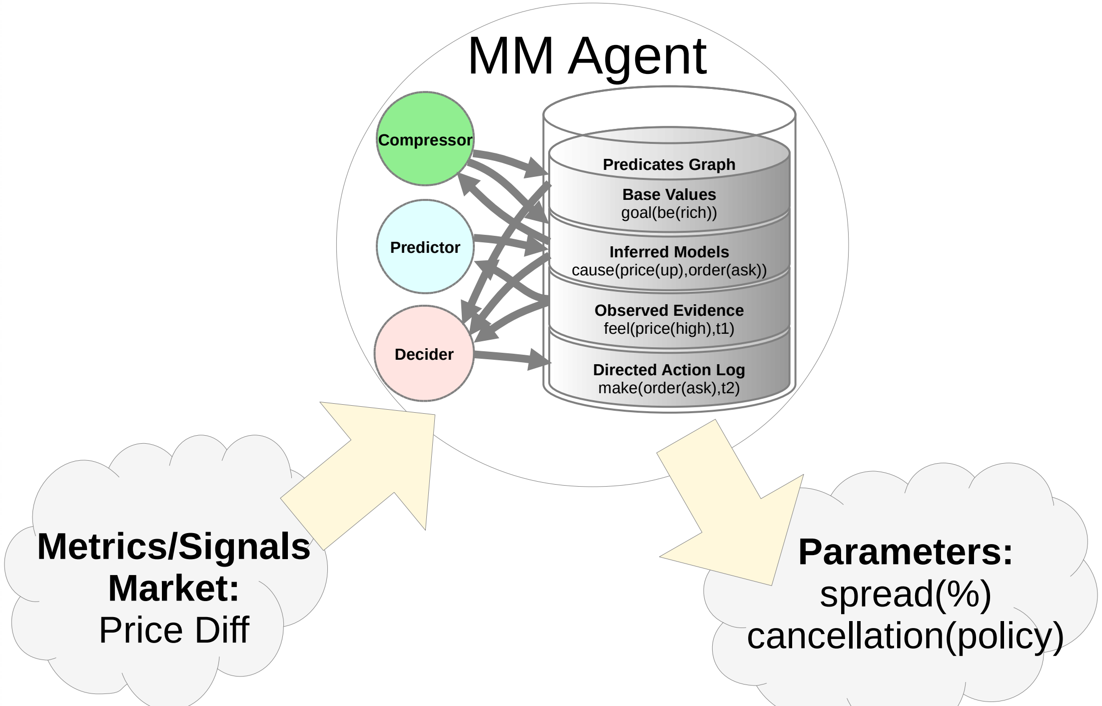
https://arxiv.org/abs/2204.13265

Operational Space for Market Making

More Metrics



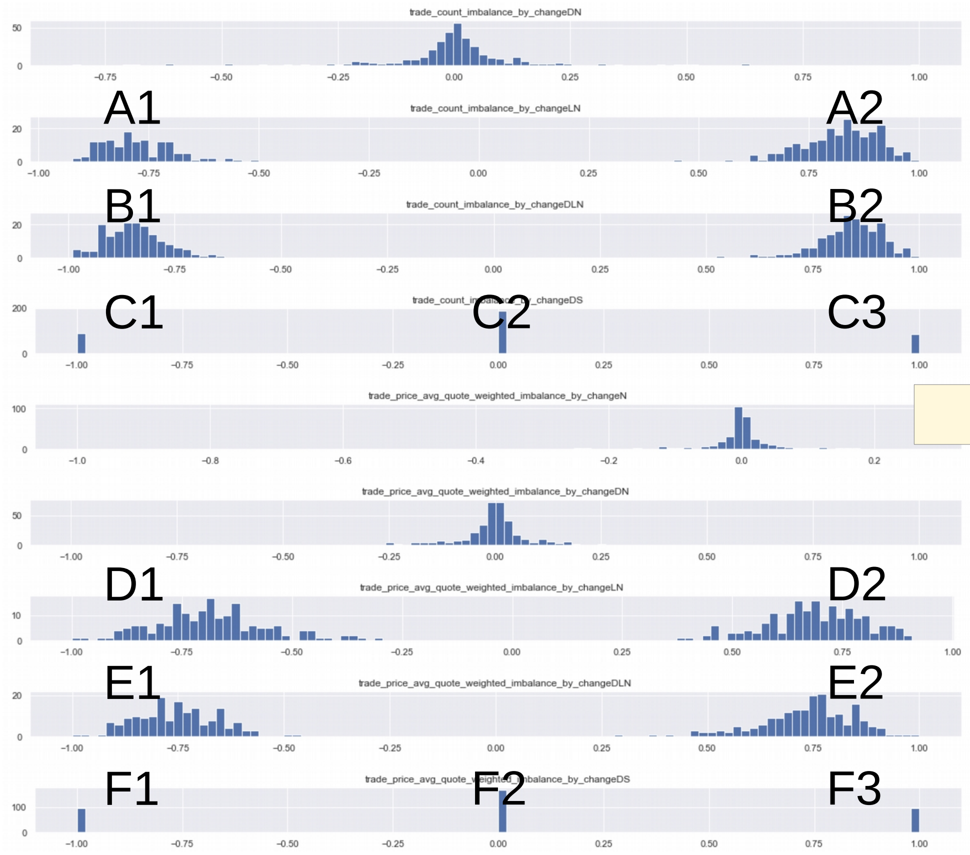
Simplified



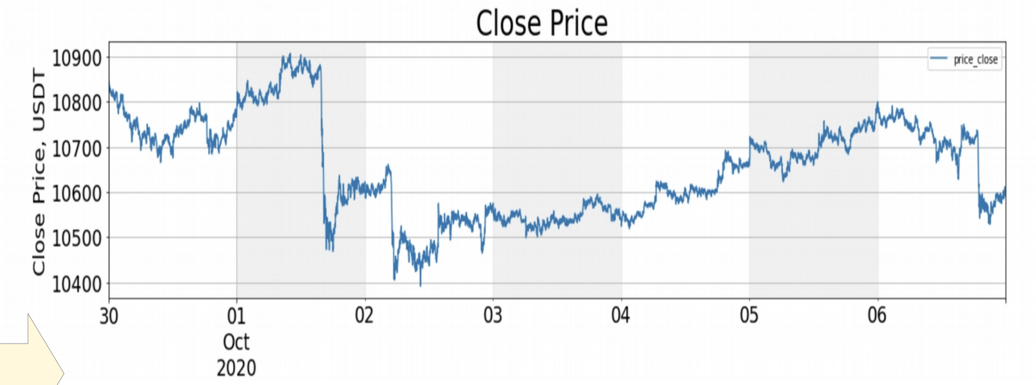
https://arxiv.org/abs/2204.13265

Symbolizing Market Conditions?

More Metrics



Flat ⇨ Crash ⇨ Crash ⇨ Flat ⇨ Up ⇨ Up ⇨ Crash



A2	A1	A1	A2	A1	A1	A1
B1	B2	B2	B1	B1	B1	B2
C2 ⇨	C1 ⇨	C1 ⇨	C2 ⇨	C3 ⇨	C3 ⇨	C1
D2	D1	D1	D2	D2	D2	D1
E2	E1	E1	E2	E2	E2	E1
F2	F1	F1	F2	F3	F3	F3

Time

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://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)

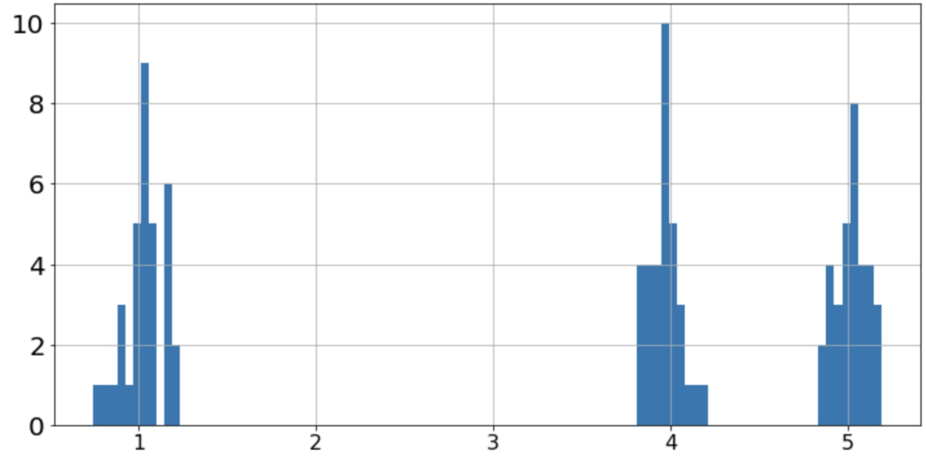
   https://www.researchgate.net/publication/221020638_Cluster_Validity_Measures_Based_on_the_Minimum_Description_Length_Principle

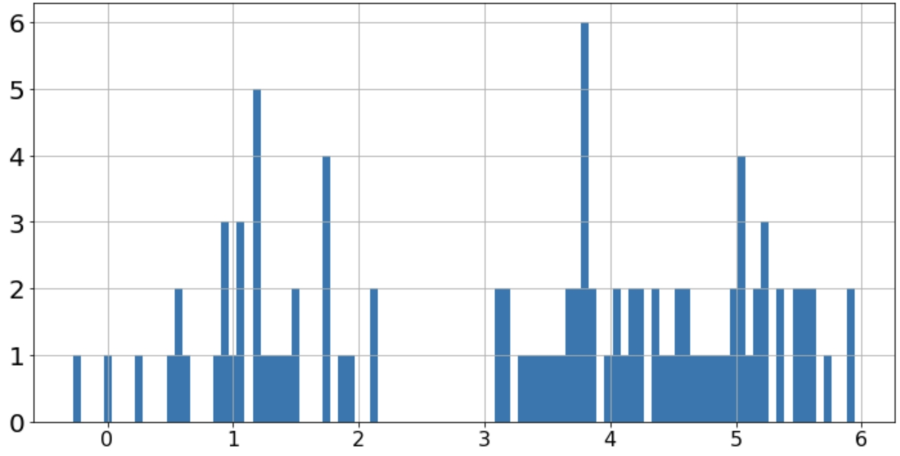
3. Minimizing "Normalized Centroid Distance times Centroids" (NCDC) - extends NCD multiplying it by number of clusters to penalize creation of too many clusters, works for K=1, more human-intuitive than NCD but less human-intuitive than SC

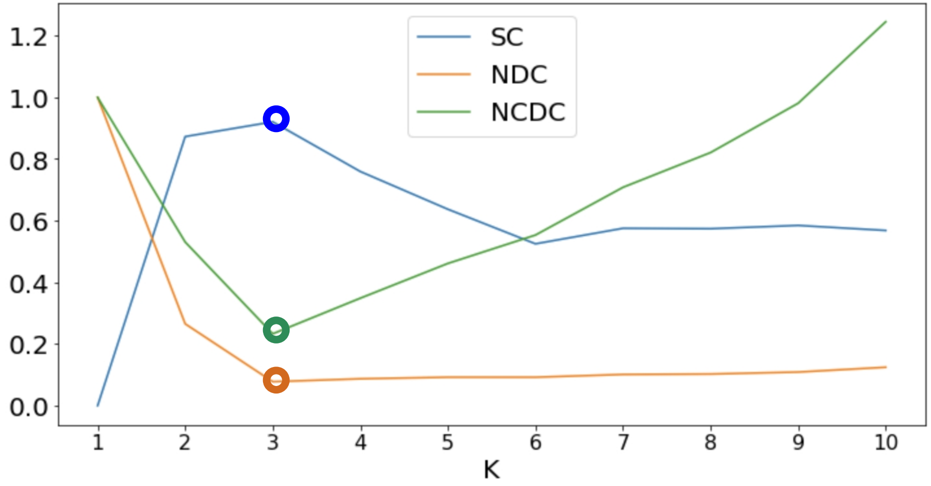
4. Using SC+ (maximize SC if it is above threshold 0.65 or minimize NCDC otherwise) - seems generally optimal from human intuition perspective

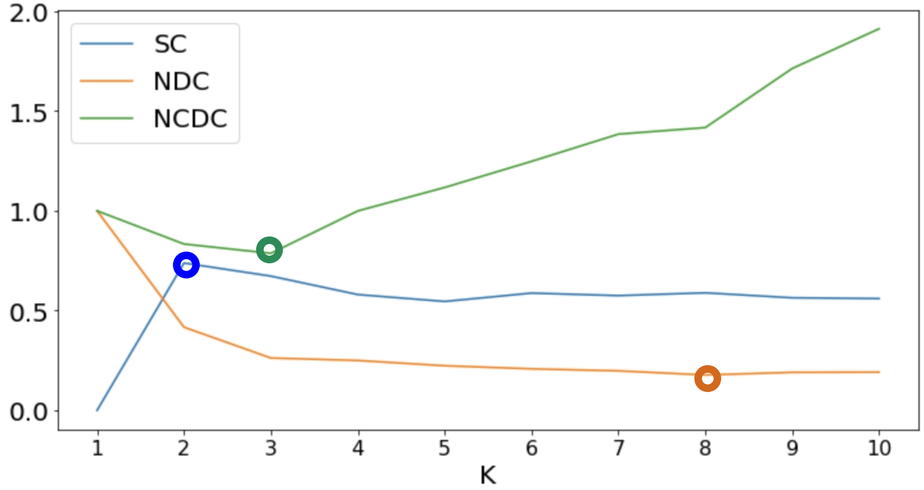
https://github.com/aigents/pygents/blob/main/notebooks/cluster/distribution_modes.ipynb

Quantification Measures





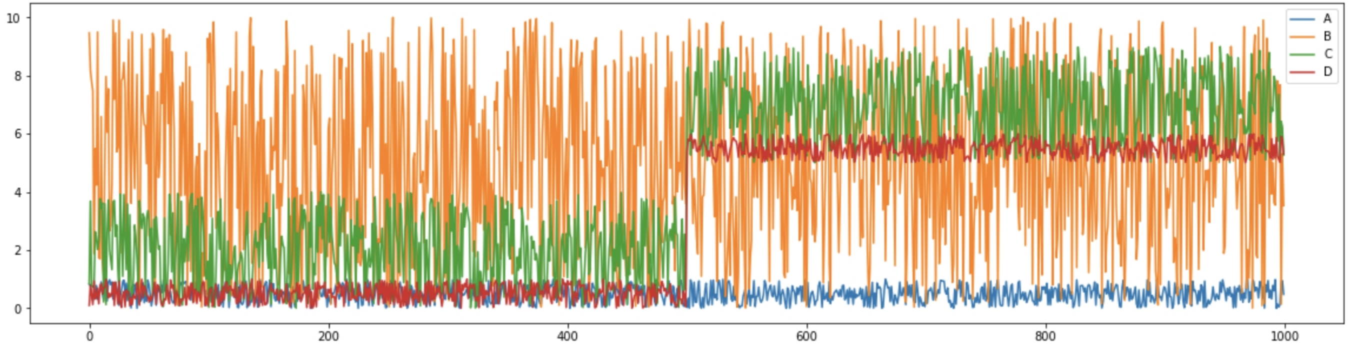




Quantification - 1

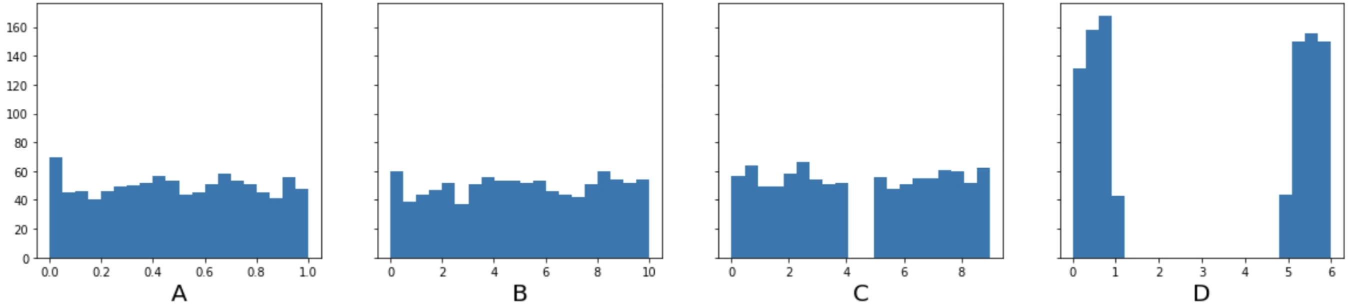
NCDC

A 1
B 3
C 2
D 2



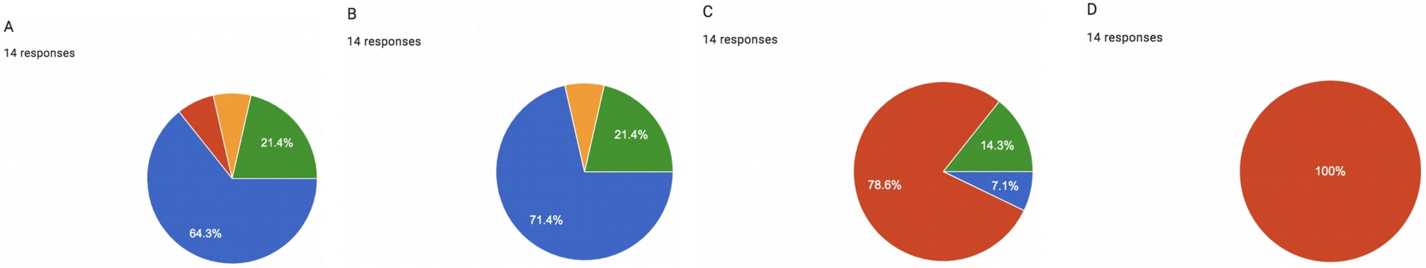
SC+

A 1
B 3
C 2
D 2



Human

A 1
B 1
C 2
D 2



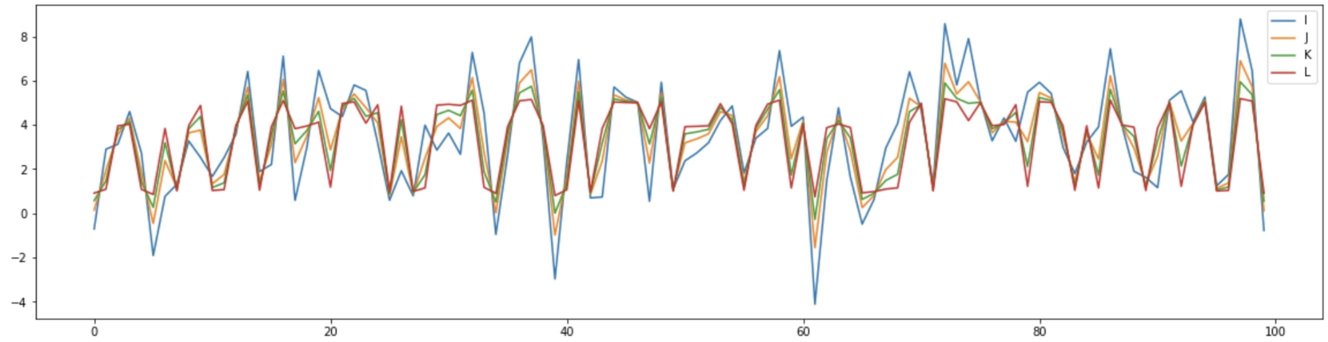
Human

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

Quantification - 2

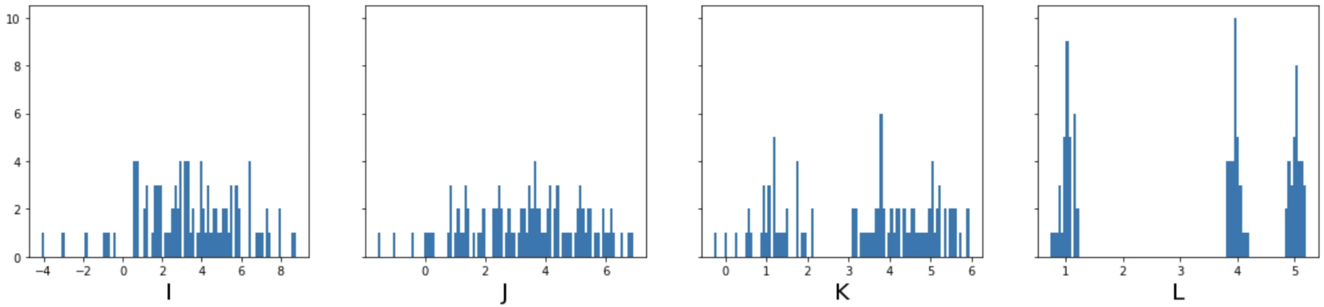
NCDC

I 1
J 1
K 3
L 3



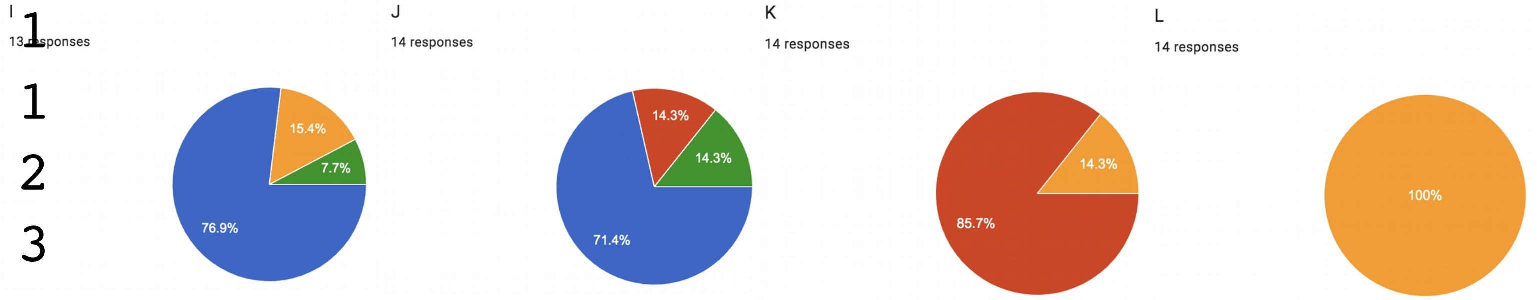
SC+

I 1
J 1
K 2
L 3



Human

I 1
J 1
K 2
L 3



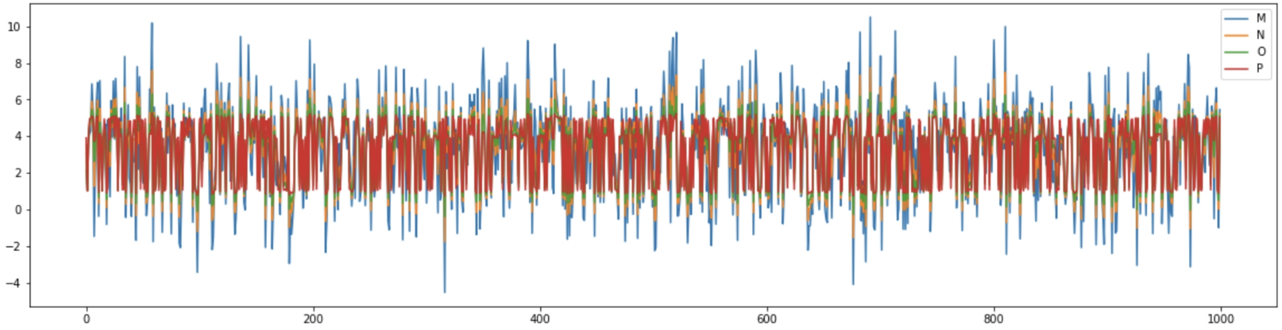
Human

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

Quantification - 3

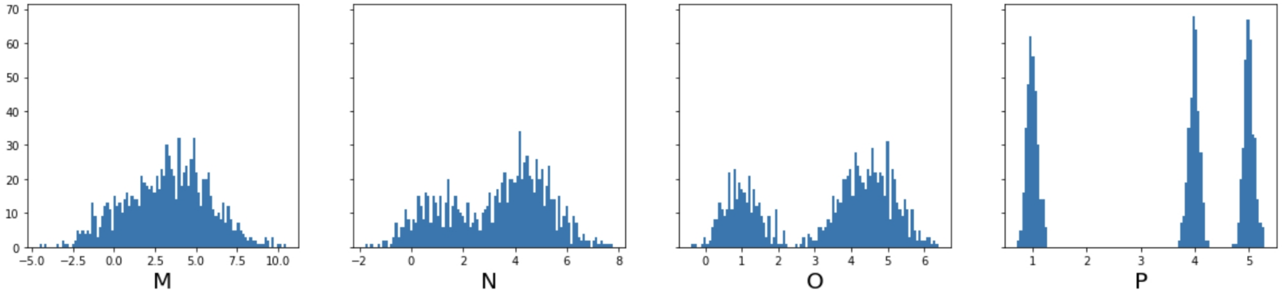
NCDC

M 1
N 2
O 2
P 3



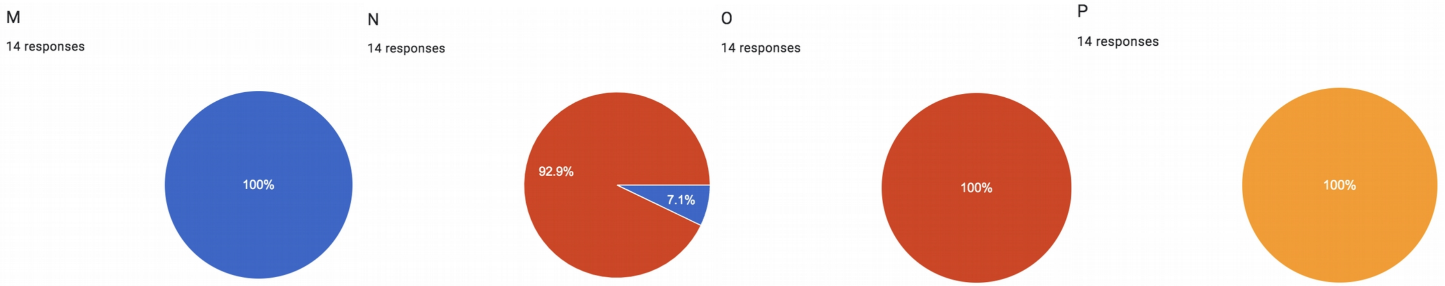
SC+

M 1
N 2
O 2
P 3



Human

M 1
N 2
O 2
P 3



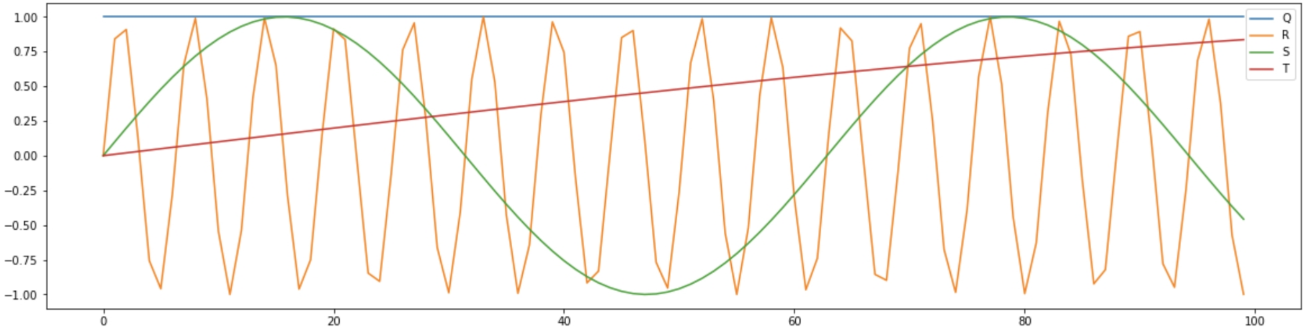
Human

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

Quantification - 4

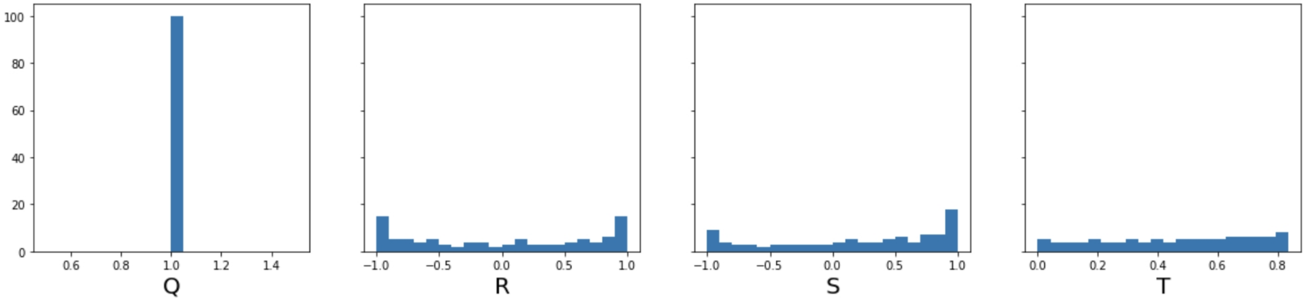
NCDC

Q 1
R 3
S 3
T 1



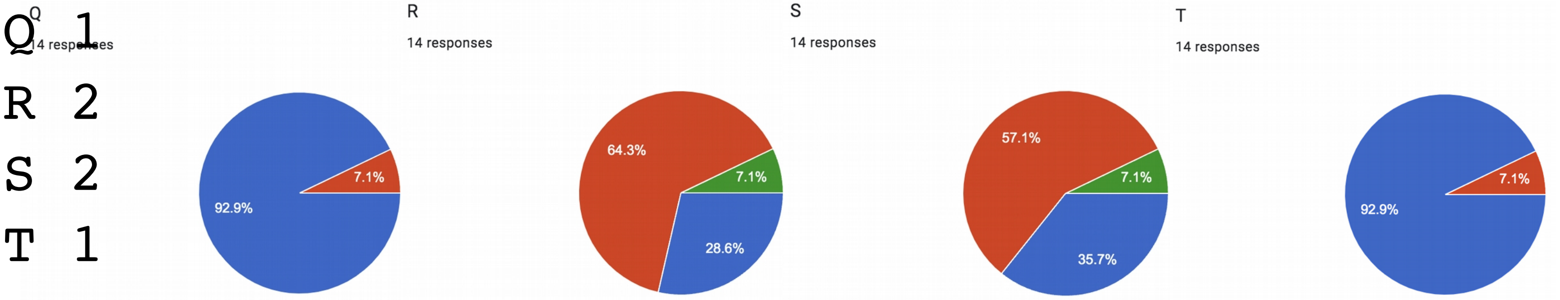
SC+

Q 1
R 2
S 2
T 1



Human

Q 1
R 2
S 2
T 1



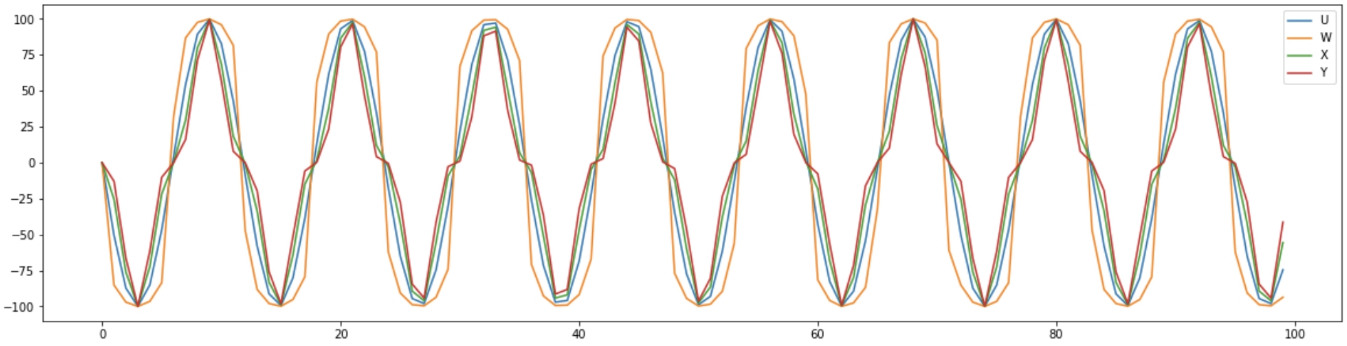
Human

1 or none
2
3
4 or more

Quantification - 5

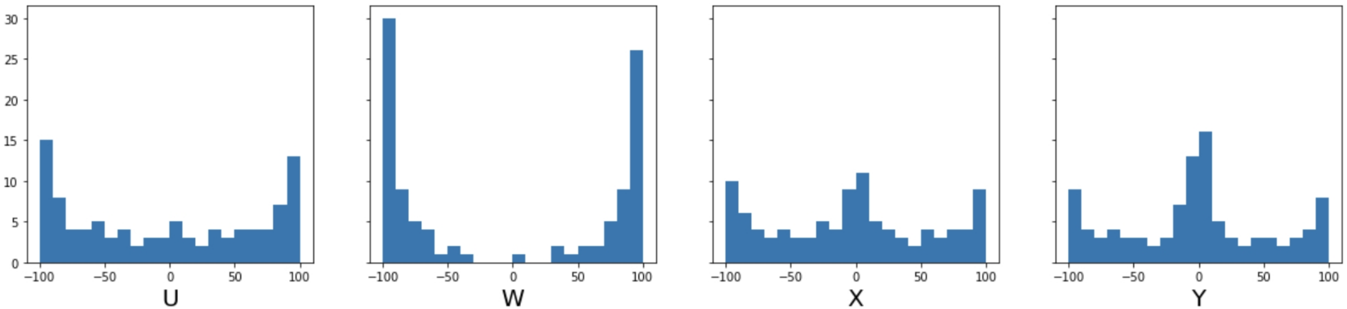
NCDC

U 3
W 2
X 1
Y 1



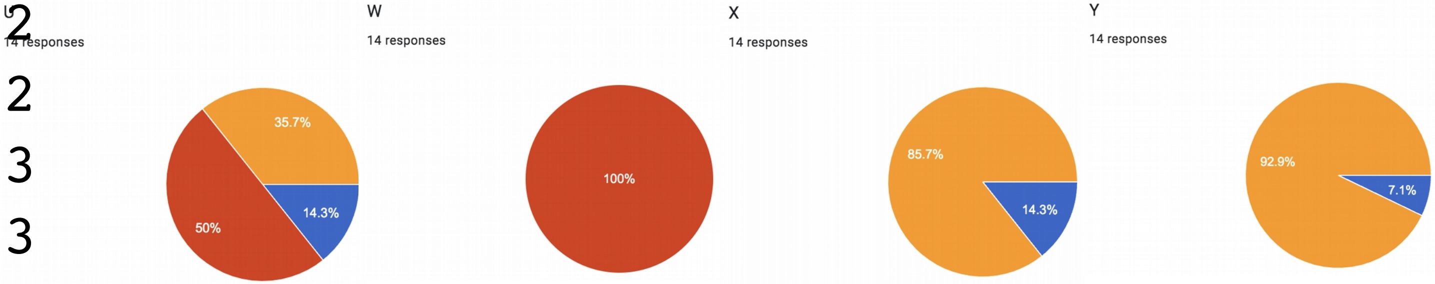
SC+

U 2
W 2
X 3
Y 3



Human

U 2
W 2
X 3
Y 3



Human

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

Quantification – 6

NCDC

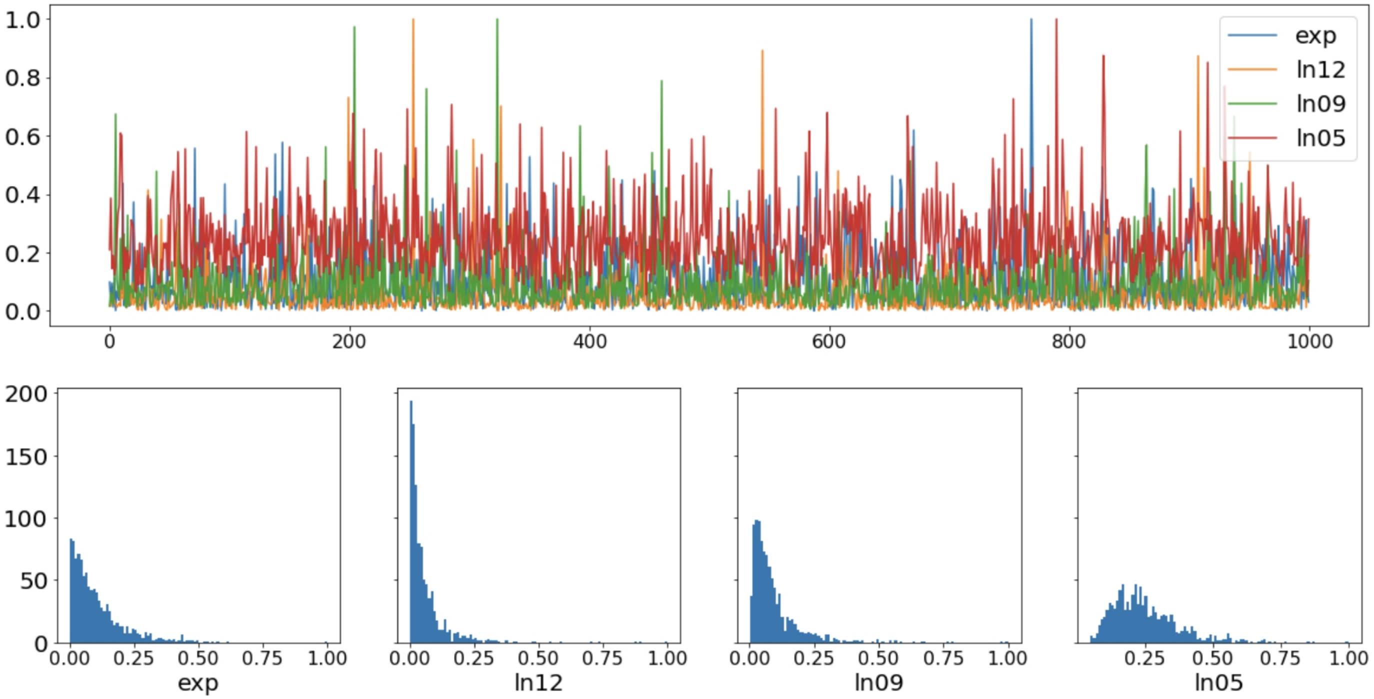
```
exp  1
ln12 1
ln09 1
ln05 1
```

SC+

```
exp  2
ln12 2
ln09 2
ln05 1
```

Human

```
exp  2
ln12 2
ln09 2
ln05 1
```



Quantification: Human vs. Machine

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

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

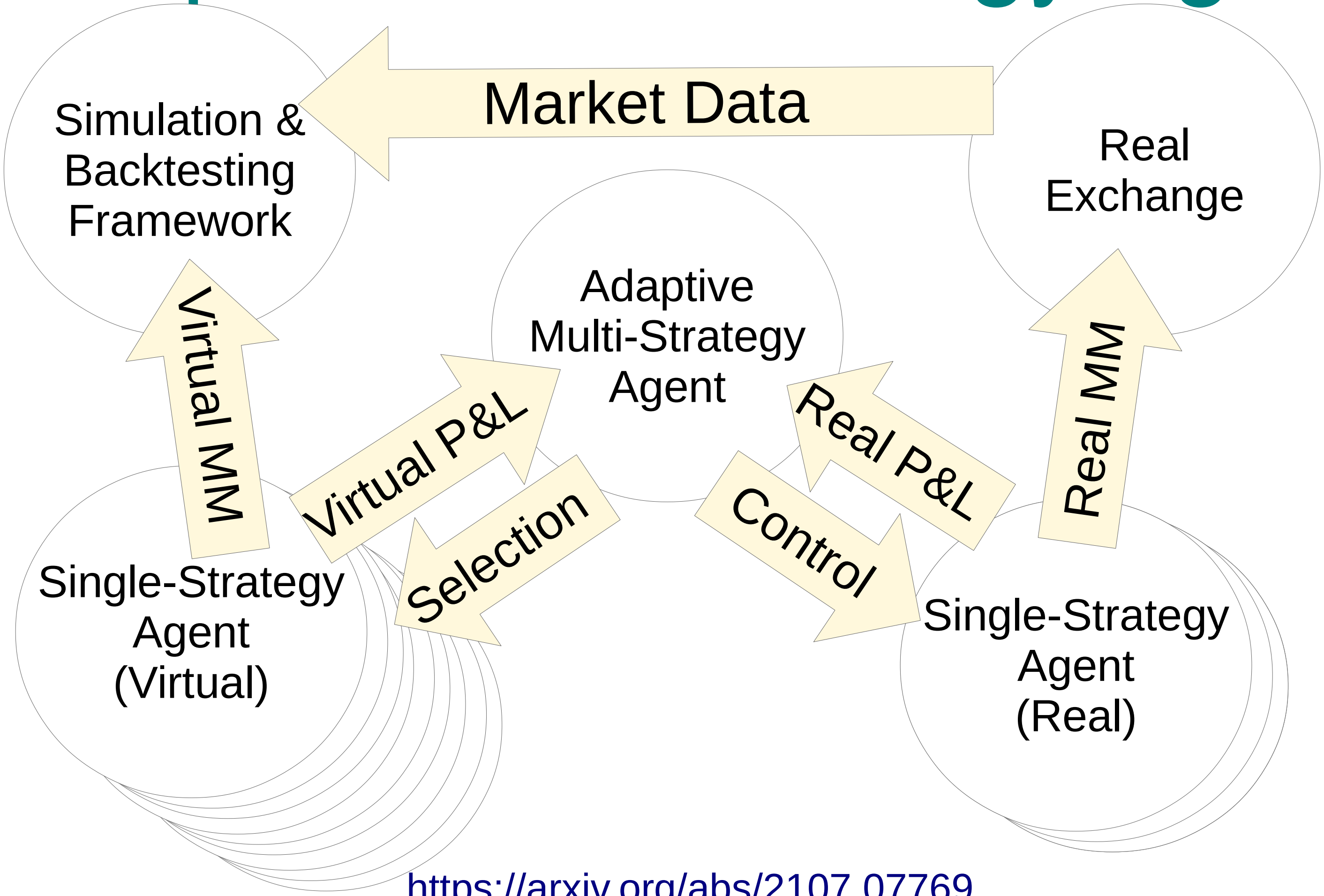
https://stackoverflow.com/questions/51919897/is-fleiss-kappa-a-reliable-measure-for-interannotator-agreement-the-following-r

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)

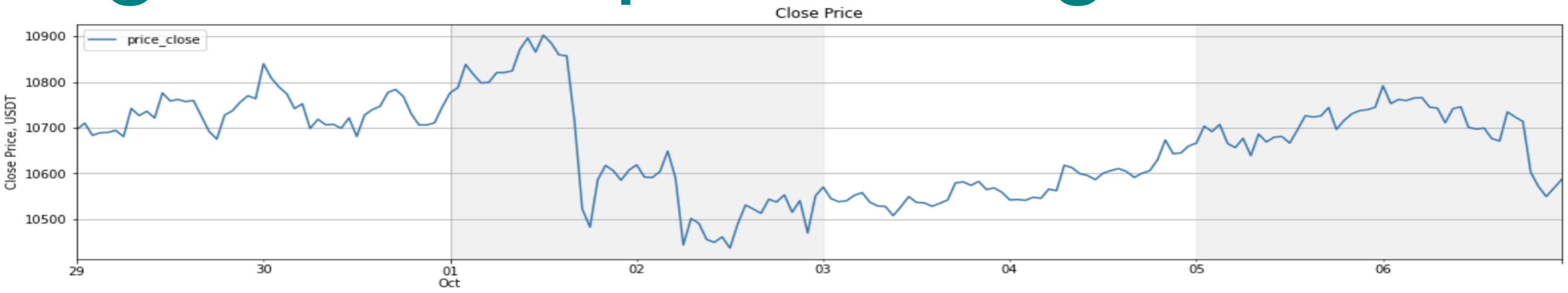
Adaptive Multi-Strategy Agent



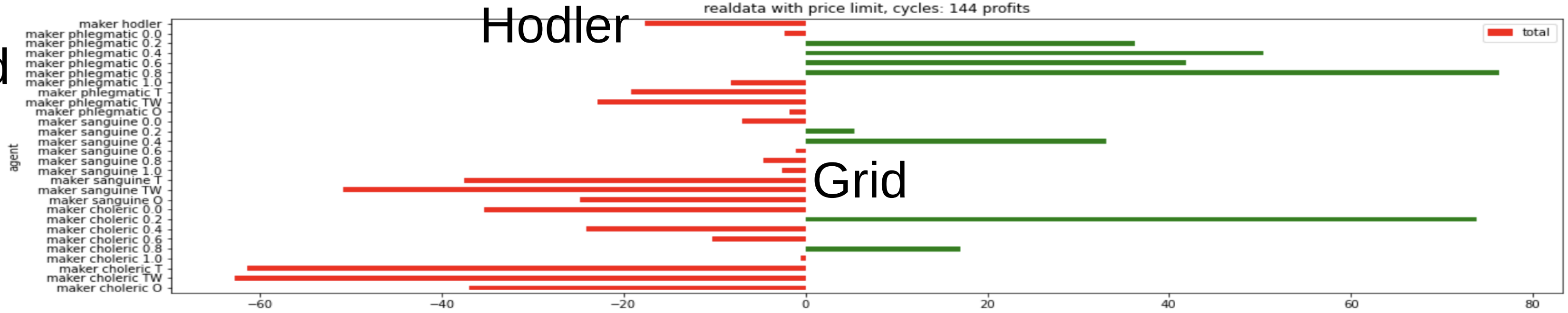
https://arxiv.org/abs/2107.07769

Trading with multiple Strategies at a Time

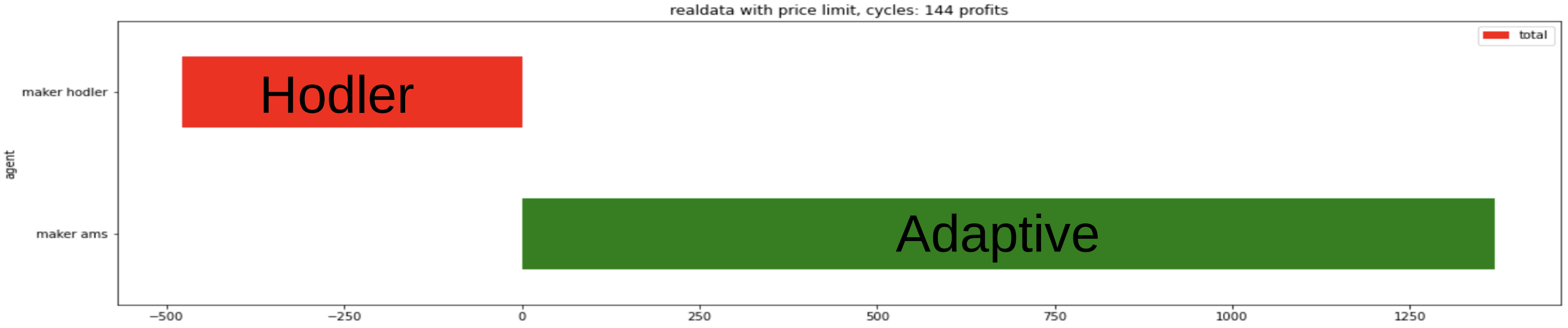
BTC/
USDT



Order Grid
Marker
Making
P & L



Adaptive
Multi
Strategy
Agent
P & L



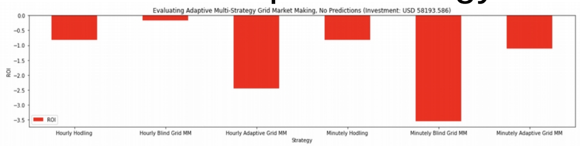
Overall ROI for adaptive MM strategy

BTC/

USDT

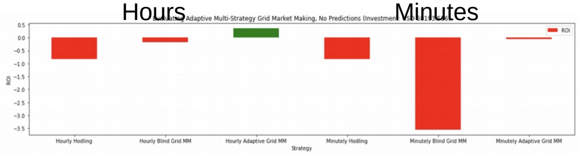
6 days testing interval

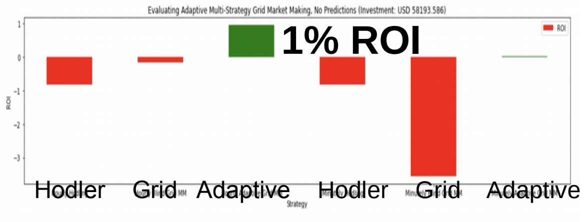
"Basic/Simple" Strategy



Hodler Grid Adaptive Hodler Grid Adaptive

Hours Minutes



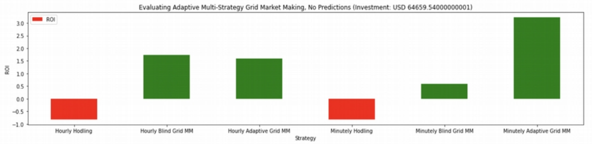


1% ROI

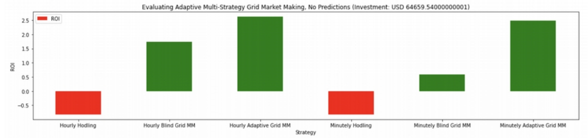
Hodler Grid Adaptive Hodler Grid Adaptive

Hours Minutes

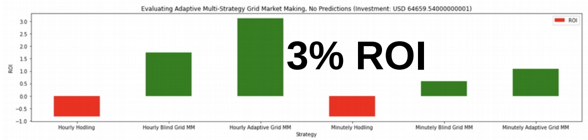
"NIOX Maker" Strategy



1 day strategy update interval (6 days)



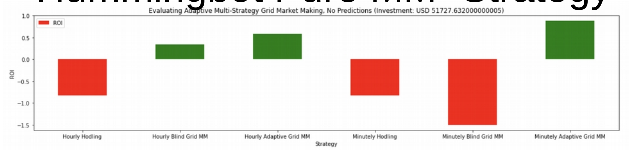
2 days strategy update interval (6 days)



3% ROI

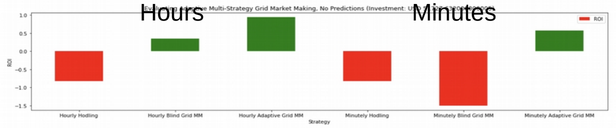
3 days strategy update interval (6 days)

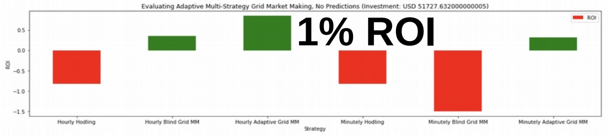
"Hummingbot Pure MM" Strategy



Hodler Grid Adaptive Hodler Grid Adaptive

Hours Minutes





1% ROI

Hodler Grid Adaptive Hodler Grid Adaptive

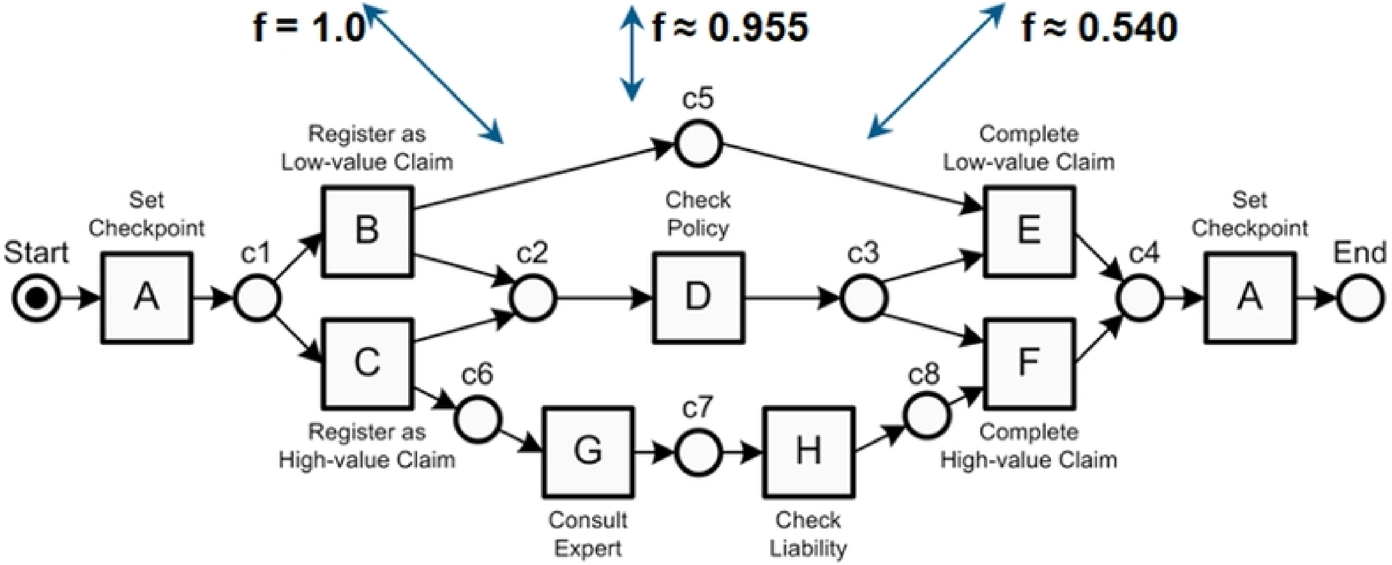
Hours Minutes

Process Mining in Business Log Data

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

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

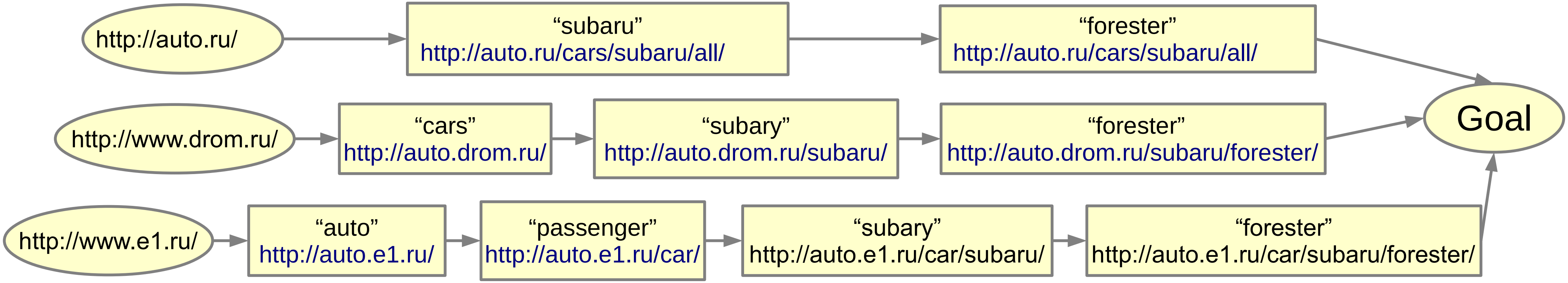
No. of Instances	Log Traces
24 7 15 6 1 8	BDE AABHF CHF ADBE ACBGDFAA ABEDA



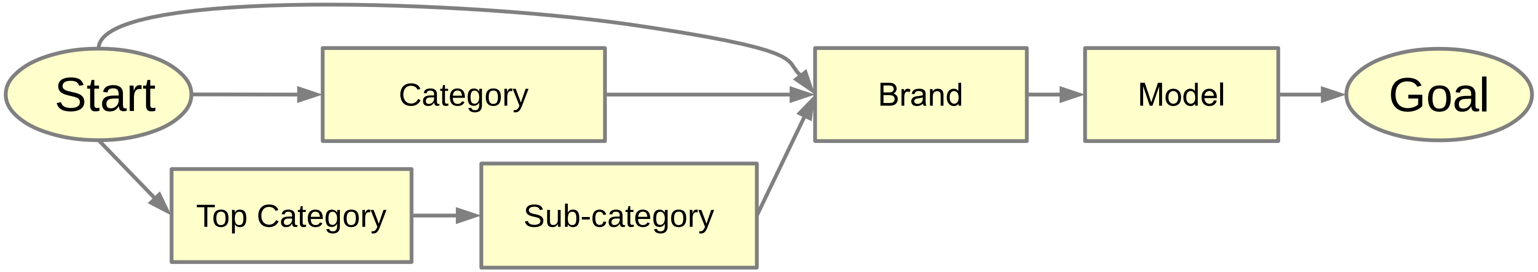
https://www.puzzledata.com/process-mining_eng/

Scenario Mining in Process Data Example

Internet navigation routes when searching for “Forester” cars



Generalized click-through scenario when searching for products



Text Grounding on Non-Text Events

Common Sense Reasoning

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

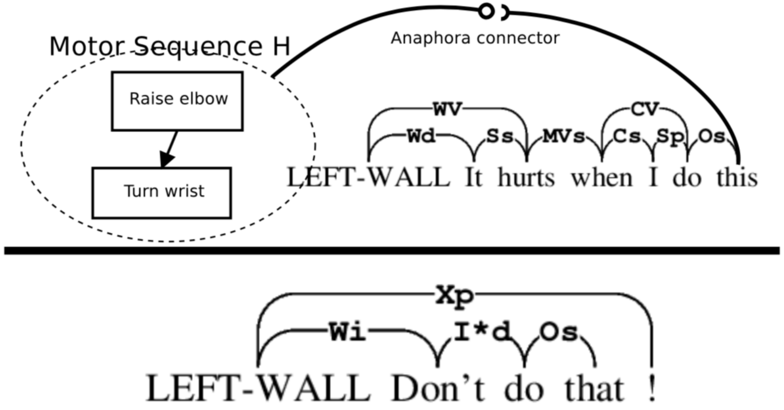
Linas Veptstas, 2021

https://arxiv.org/abs/1901.01341

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

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

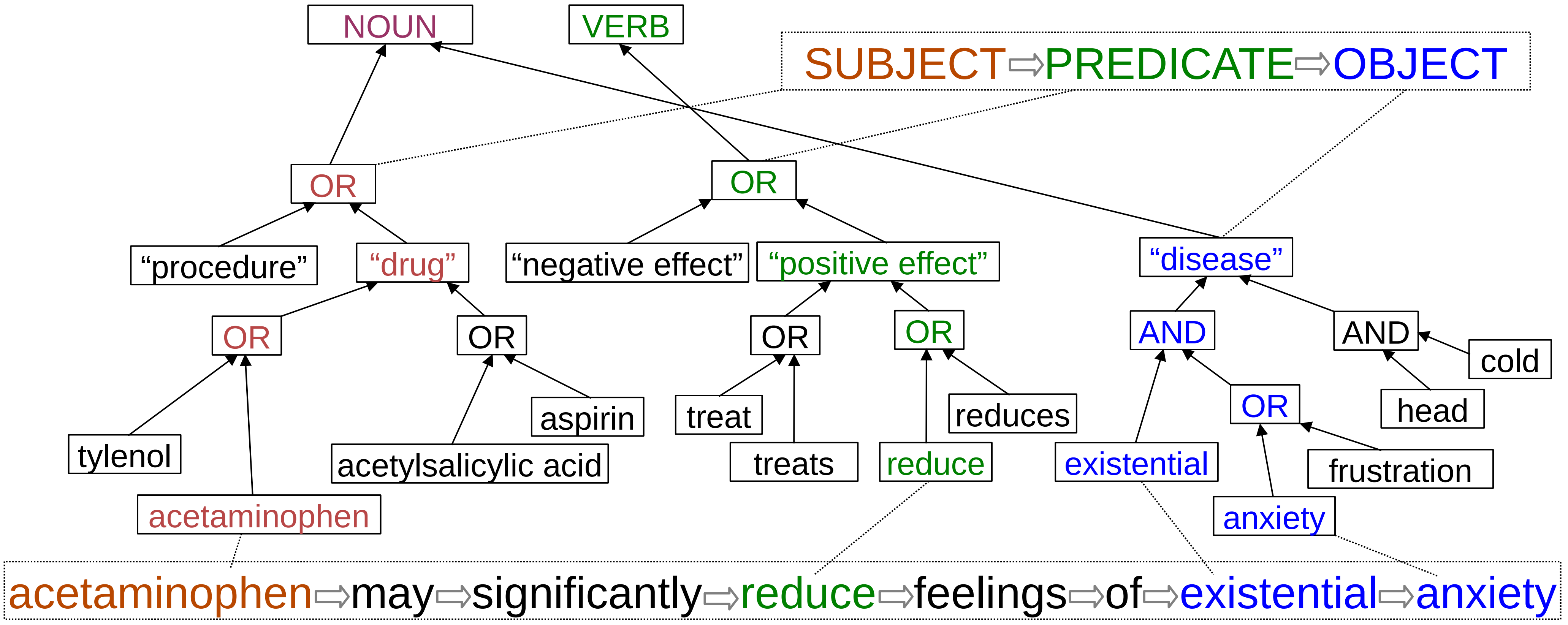
$$\frac{A \wedge A \rightarrow B}{B}$$



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

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

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/

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

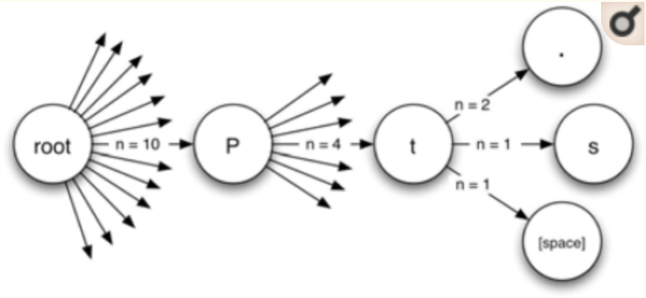


Figure 1

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

Metrics/Indicators:

Mutual Information[1]

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)

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.

is/are

The roses _?_ Simple: no attractors

The roses in the vase _?_ Harder: 1 attractor

The roses in the vase by the door _?_ 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:

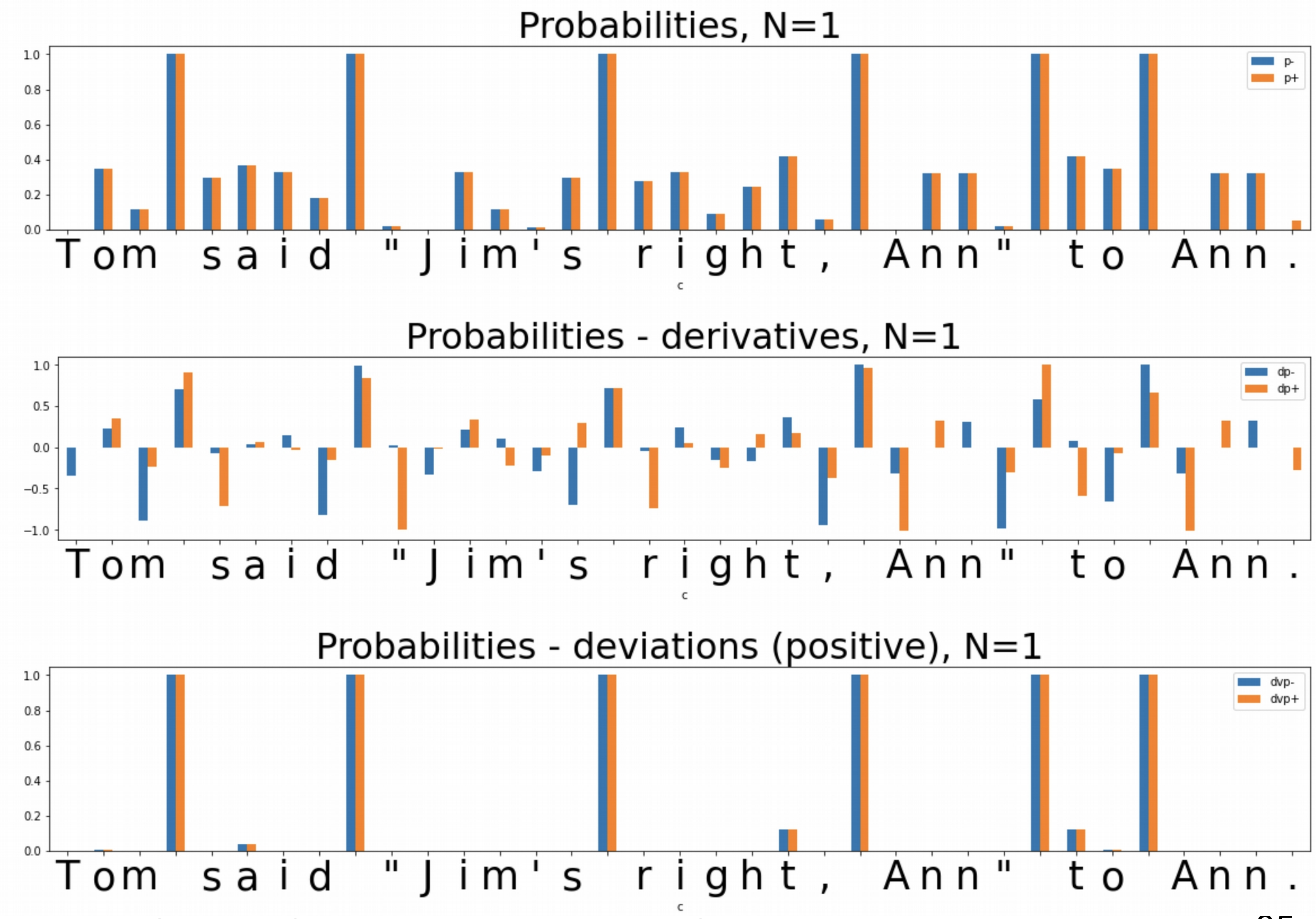
Combination of Ngram ranks N ([1],[2],[3],[1,2],[1,2,3],…)
Threshold for model compression
Threshold for segmentation

Evaluations:

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

Unsupervised Text Segmentation (Tokenization)

Metrics/Indicators:
Ngram (Character)
Probability



Unsupervised Text Segmentation (Tokenization)

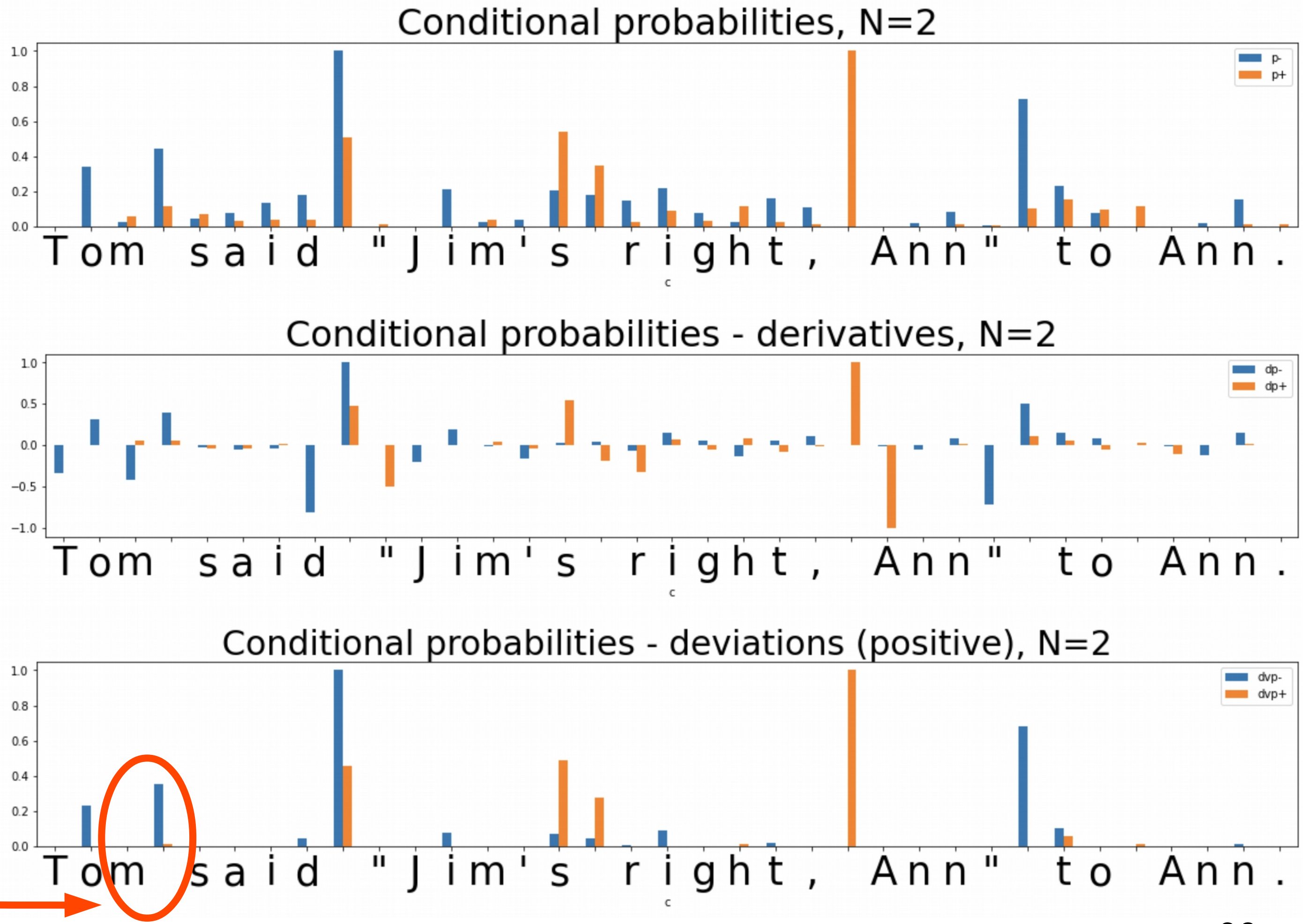
Metrics/Indicators:

Ngram (Character) Conditional Probability

(of Transition)

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

$P(\text{“m ”})/P(\text{“m”})$



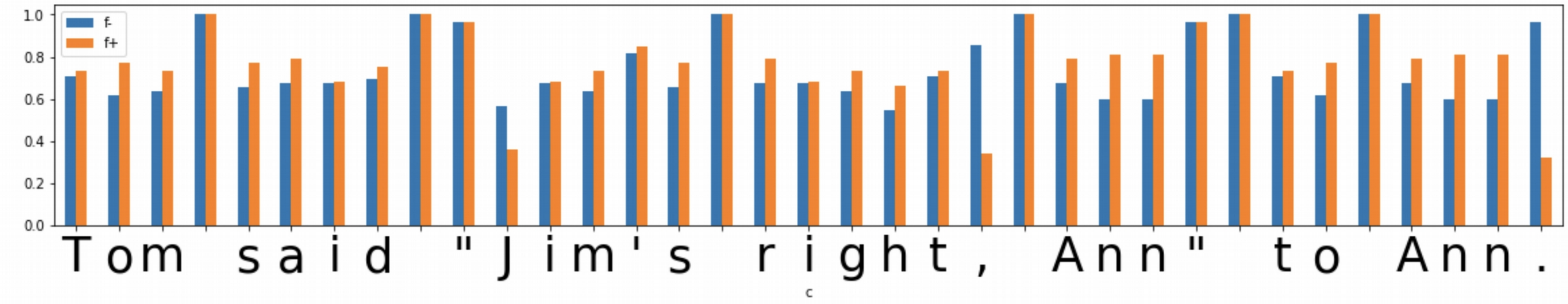
Unsupervised Text Segmentation (Tokenization)

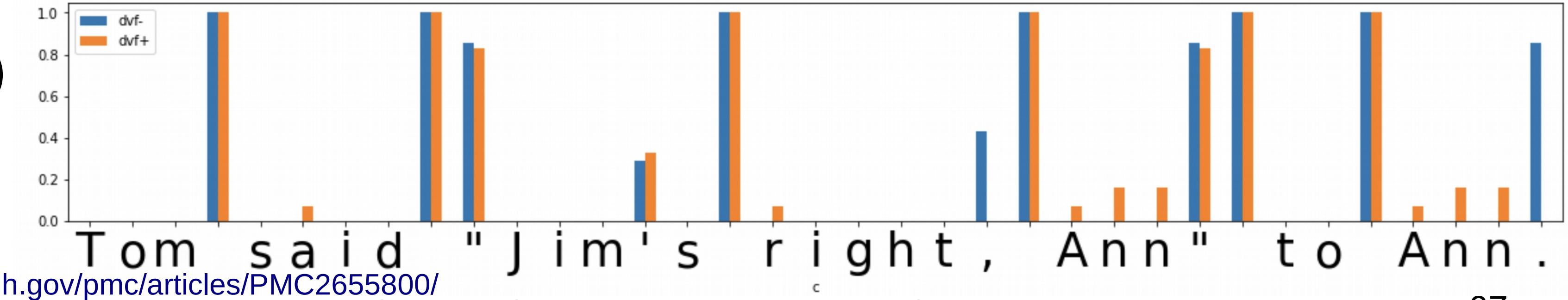
Metrics/ Indicators:

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/

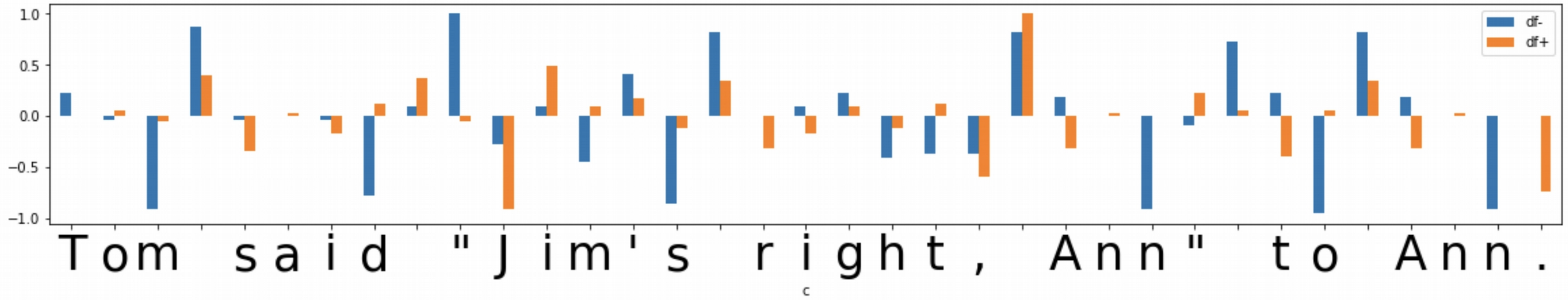
Unsupervised Text Segmentation (Tokenization)

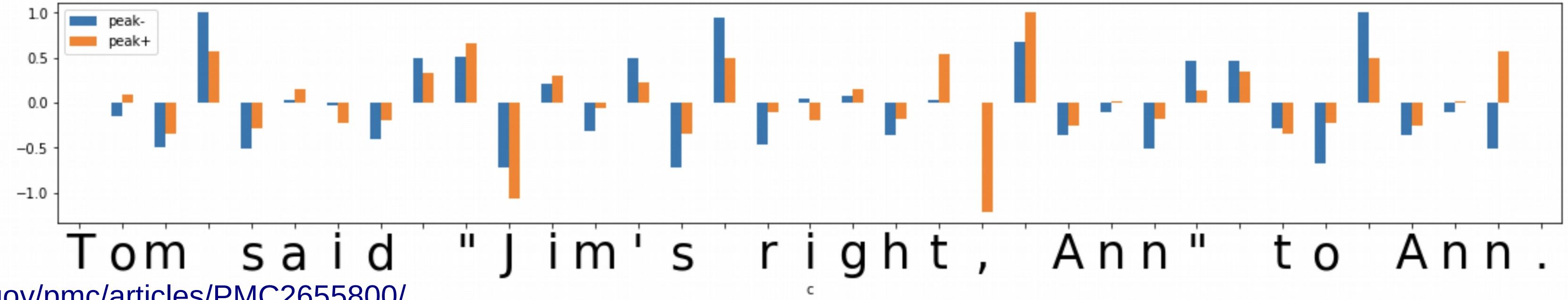
Metrics/ Indicators:

Transition Freedom Derivative and “Peak”

(Freedom of Transition “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
```





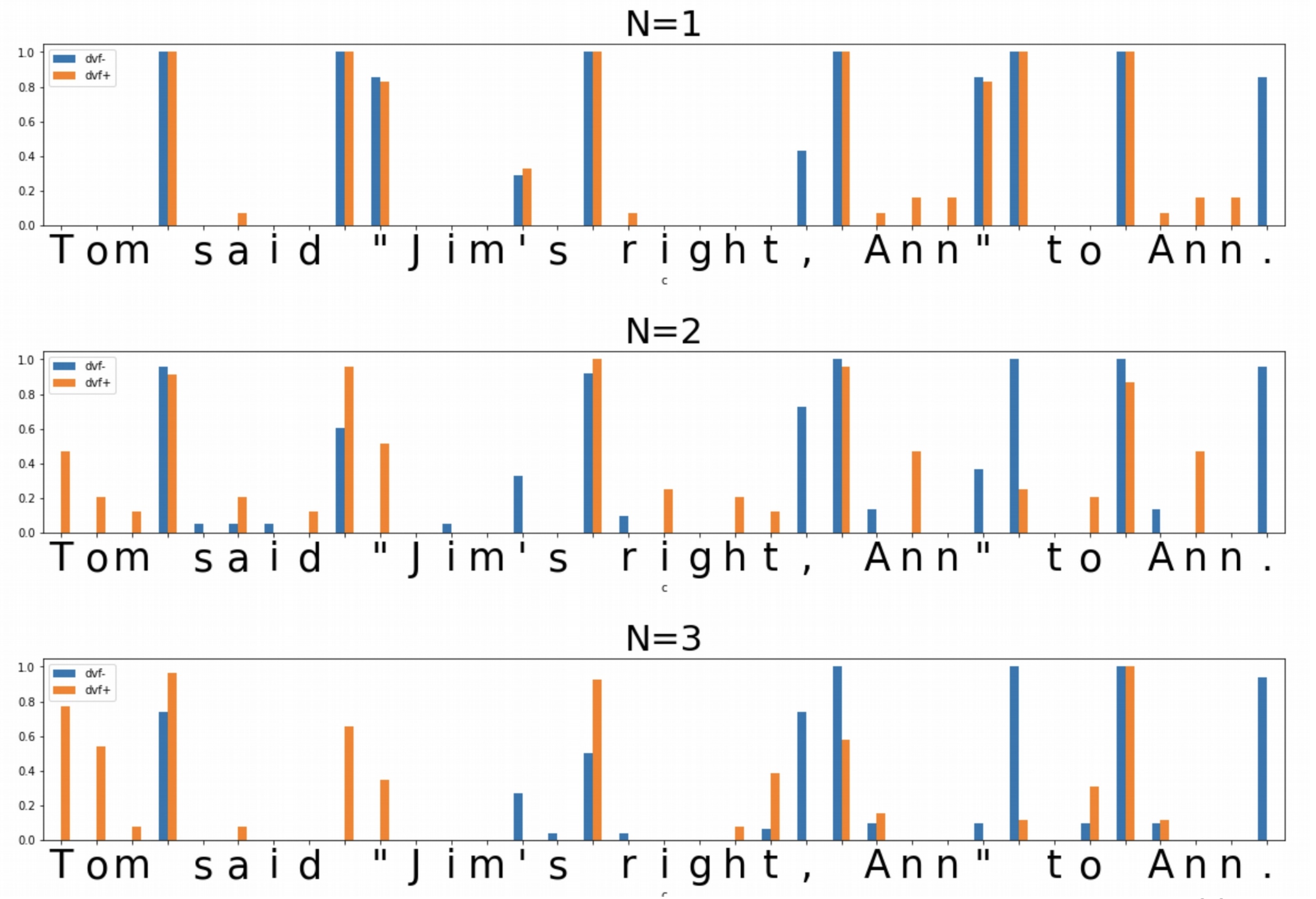
https://www.ncbi.nlm.nih.gov/pmc/articles/PMC2655800/

Unsupervised Text Segmentation (Tokenization)

Metrics/ Indicators:

Transition Freedom Deviation

(varying "N")



Unsupervised Text Segmentation (Tokenization)

English

Hyper-Parameters:

TF

Threshold for model compression

Combination of Ngram N-s

Threshold for segmentation

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

	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
[1]	0.5	0.75	0.82	0.79	0.79	0.81	0.89	0.89	0.89
[2]	0.46	0.54	0.62	0.67	0.85	0.92	0.81	0.71	0.37
[3]	0.56	0.67	0.72	0.73	0.69	0.61	0.46	0.36	0.19
[4]	0.54	0.68	0.7	0.6	0.43	0.3	0.19	0.15	0.1
[5]	0.51	0.55	0.52	0.38	0.25	0.16	0.11	0.1	0.08
[6]	0.48	0.46	0.38	0.25	0.17	0.12	0.1	0.08	0.07
[7]	0.42	0.34	0.24	0.15	0.11	0.1	0.08	0.08	0.07
[1, 2]	0.47	0.58	0.82	0.94	0.94	0.91	0.89	0.79	0.56
[2, 3]	0.51	0.62	0.74	0.79	0.83	0.81	0.66	0.46	0.24
[1, 2, 3]	0.5	0.69	0.79	0.87	0.91	0.89	0.78	0.58	0.25
[1, 2, 3, 4]	0.55	0.75	0.84	0.86	0.84	0.75	0.52	0.31	0.15
[4, 5, 6, 7]	0.56	0.6	0.51	0.33	0.2	0.14	0.1	0.08	0.07
[1, 2, 3, 4, 5]	0.56	0.78	0.86	0.84	0.74	0.53	0.31	0.17	0.1
[1, 2, 3, 4, 5, 6, 7]	0.59	0.78	0.82	0.69	0.49	0.26	0.15	0.09	0.07

F1 - Brown ddf- & ddf+ filter=0.0001 parameters=864370

	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
[1]	0.73	0.96	0.98	0.99	0.96	0.94	0.95	0.95	0.89
[2]	0.46	0.54	0.64	0.79	0.91	0.94	0.89	0.7	0.44
[3]	0.55	0.66	0.74	0.78	0.72	0.65	0.49	0.37	0.19
[4]	0.54	0.67	0.7	0.61	0.45	0.32	0.21	0.16	0.1
[5]	0.51	0.55	0.52	0.38	0.26	0.17	0.12	0.1	0.08
[6]	0.48	0.46	0.38	0.26	0.18	0.13	0.1	0.09	0.07
[7]	0.42	0.35	0.25	0.16	0.12	0.1	0.09	0.08	0.08
[1, 2]	0.51	0.64	0.82	0.96	0.96	0.96	0.9	0.88	0.68
[2, 3]	0.5	0.62	0.74	0.85	0.89	0.86	0.71	0.51	0.27
[1, 2, 3]	0.53	0.69	0.81	0.91	0.93	0.92	0.82	0.6	0.36
[1, 2, 3, 4]	0.55	0.75	0.86	0.88	0.88	0.81	0.57	0.33	0.17
[4, 5, 6, 7]	0.56	0.6	0.52	0.35	0.22	0.15	0.1	0.09	0.07
[1, 2, 3, 4, 5]	0.57	0.79	0.88	0.86	0.78	0.59	0.33	0.18	0.1
[1, 2, 3, 4, 5, 6, 7]	0.59	0.79	0.83	0.71	0.5	0.28	0.16	0.09	0.08

Unsupervised Text Segmentation (Tokenization)

Chinese

Hyper-Parameters:

TF

Threshold for model compression

Combination of Ngram N-s

Threshold for segmentation

F1 - Train(Large) f- & f+ filter=0 parameters=249859247

	0	0.0005	0.001	0.005	0.01	0.02	0.05	0.1	0.15	0.2	0.3	0.4	0.5	0.8
[1]	0.33	0.33	0.33	0.33	0.33	0.33	0.33	0.33	0.33	0.34	0.4	0.43	0.4	0.22
[2]	0.33	0.33	0.33	0.33	0.35	0.38	0.44	0.49	0.54	0.54	0.51	0.48	0.41	0.19
[1, 2]	0.33	0.33	0.33	0.33	0.33	0.33	0.33	0.33	0.33	0.35	0.44	0.48	0.46	0.26

F1 - Train(Large) f- & f+ filter=0.0001 parameters=231751412

	0	0.0005	0.001	0.005	0.01	0.02	0.05	0.1	0.15	0.2	0.3	0.4	0.5	0.8
[1]	0.33	0.33	0.33	0.33	0.33	0.33	0.33	0.34	0.34	0.37	0.43	0.51	0.49	0.35
[2]	0.33	0.33	0.33	0.33	0.34	0.37	0.44	0.5	0.55	0.6	0.6	0.56	0.49	0.25
[1, 2]	0.33	0.33	0.33	0.33	0.33	0.33	0.33	0.34	0.37	0.42	0.54	0.61	0.54	0.31

F1 - Train(Large) f- & f+ filter=0.001 parameters=196866127

	0	0.0005	0.001	0.005	0.01	0.02	0.05	0.1	0.15	0.2	0.3	0.4	0.5	0.8
[1]	0.33	0.33	0.33	0.33	0.33	0.33	0.34	0.37	0.42	0.47	0.5	0.47	0.41	0.31
[2]	0.33	0.33	0.33	0.33	0.34	0.38	0.46	0.55	0.61	0.63	0.58	0.48	0.42	0.2
[1, 2]	0.33	0.33	0.33	0.33	0.33	0.33	0.34	0.39	0.48	0.56	0.57	0.52	0.45	0.27

F1 - Train(Large) f- & f+ filter=0.01 parameters=123792046

	0	0.0005	0.001	0.005	0.01	0.02	0.05	0.1	0.15	0.2	0.3	0.4	0.5	0.8
[1]	0.33	0.33	0.33	0.33	0.33	0.34	0.38	0.48	0.49	0.48	0.41	0.38	0.34	0.3
[2]	0.33	0.33	0.33	0.33	0.34	0.38	0.48	0.58	0.6	0.58	0.49	0.41	0.34	0.16
[1, 2]	0.33	0.33	0.33	0.33	0.33	0.34	0.39	0.51	0.57	0.54	0.47	0.41	0.36	0.23

F1 - Train(Large) f- & f+ filter=0.1 parameters=51791264

	0	0.0005	0.001	0.005	0.01	0.02	0.05	0.1	0.15	0.2	0.3	0.4	0.5	0.8
[1]	0.33	0.33	0.33	0.33	0.33	0.34	0.38	0.43	0.46	0.41	0.36	0.32	0.32	0.21
[2]	0.33	0.33	0.33	0.33	0.33	0.34	0.4	0.49	0.52	0.5	0.43	0.36	0.29	0.16
[1, 2]	0.33	0.33	0.33	0.33	0.33	0.33	0.37	0.46	0.49	0.5	0.41	0.35	0.33	0.19

Unsupervised Text Segmentation (Tokenization)

Chinese

Hyper-Parameters:

TF “Peak”

Threshold for model compression

Combination of Ngram N-s

Threshold for segmentation

F1 - Train(Large) peak- & peak+ filter=0 parameters=249859247

	0	0.0005	0.001	0.005	0.01	0.02	0.05	0.1	0.15	0.2	0.3	0.4	0.5	0.8
[1]	0.48	0.48	0.49	0.49	0.49	0.49	0.49	0.48	0.46	0.42	0.37	0.32	0.3	0.18
[2]	0.68	0.68	0.68	0.68	0.68	0.68	0.67	0.66	0.63	0.6	0.53	0.44	0.35	0.17
[1, 2]	0.65	0.65	0.65	0.65	0.65	0.65	0.66	0.64	0.63	0.6	0.52	0.42	0.35	0.2

F1 - Train(Large) peak- & peak+ filter=0.0001 parameters=231751412

	0	0.0005	0.001	0.005	0.01	0.02	0.05	0.1	0.15	0.2	0.3	0.4	0.5	0.8
[1]	0.58	0.58	0.58	0.58	0.58	0.57	0.57	0.56	0.56	0.53	0.5	0.43	0.37	0.23
[2]	0.7	0.7	0.7	0.7	0.7	0.7	0.69	0.68	0.66	0.65	0.57	0.48	0.38	0.18
[1, 2]	0.68	0.68	0.68	0.68	0.68	0.68	0.67	0.66	0.64	0.61	0.55	0.45	0.39	0.21

F1 - Train(Large) peak- & peak+ filter=0.001 parameters=196866127

	0	0.0005	0.001	0.005	0.01	0.02	0.05	0.1	0.15	0.2	0.3	0.4	0.5	0.8
[1]	0.58	0.58	0.58	0.58	0.57	0.57	0.57	0.55	0.53	0.49	0.43	0.37	0.32	0.24
[2]	0.71	0.71	0.71	0.71	0.71	0.71	0.71	0.68	0.65	0.58	0.48	0.39	0.33	0.17
[1, 2]	0.66	0.66	0.66	0.66	0.66	0.66	0.66	0.62	0.59	0.55	0.46	0.38	0.34	0.21

F1 - Train(Large) peak- & peak+ filter=0.01 parameters=123792046

	0	0.0005	0.001	0.005	0.01	0.02	0.05	0.1	0.15	0.2	0.3	0.4	0.5	0.8
[1]	0.55	0.55	0.55	0.55	0.55	0.55	0.54	0.5	0.47	0.43	0.35	0.32	0.29	0.25
[2]	0.69	0.68	0.68	0.68	0.68	0.68	0.66	0.61	0.55	0.49	0.4	0.33	0.27	0.16
[1, 2]	0.62	0.62	0.62	0.63	0.62	0.61	0.62	0.57	0.51	0.48	0.41	0.34	0.3	0.2

F1 - Train(Large) peak- & peak+ filter=0.1 parameters=51791264

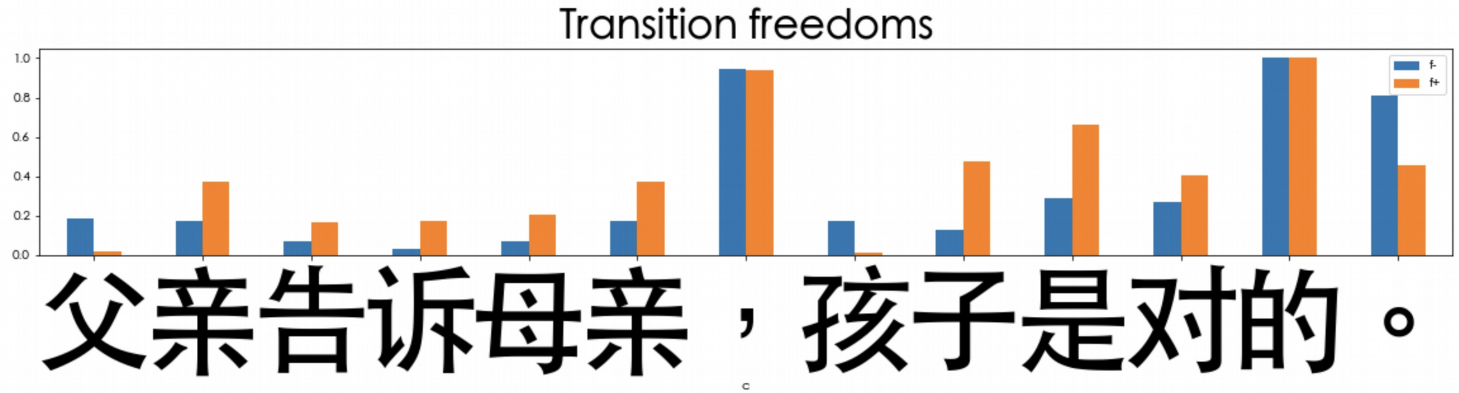
	0	0.0005	0.001	0.005	0.01	0.02	0.05	0.1	0.15	0.2	0.3	0.4	0.5	0.8
[1]	0.51	0.51	0.51	0.51	0.52	0.52	0.5	0.44	0.39	0.35	0.31	0.29	0.28	0.17
[2]	0.62	0.61	0.61	0.62	0.62	0.62	0.6	0.53	0.47	0.43	0.35	0.28	0.22	0.14
[1, 2]	0.59	0.58	0.58	0.59	0.59	0.58	0.56	0.51	0.46	0.41	0.33	0.29	0.27	0.18

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
```

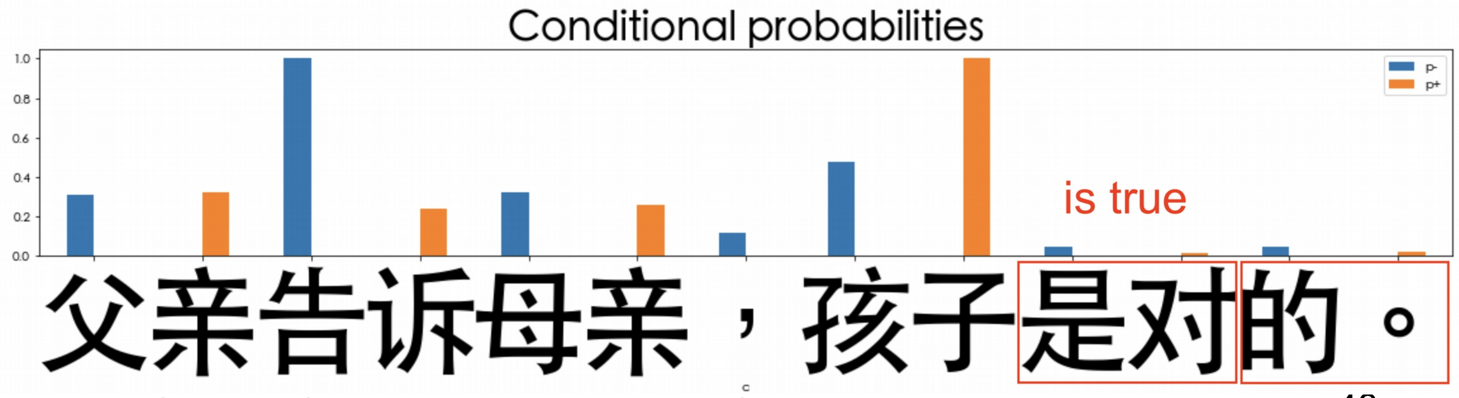
Metrics/Indicators:

Transition Freedom Deviation



Conditional Probability

(of Transition)



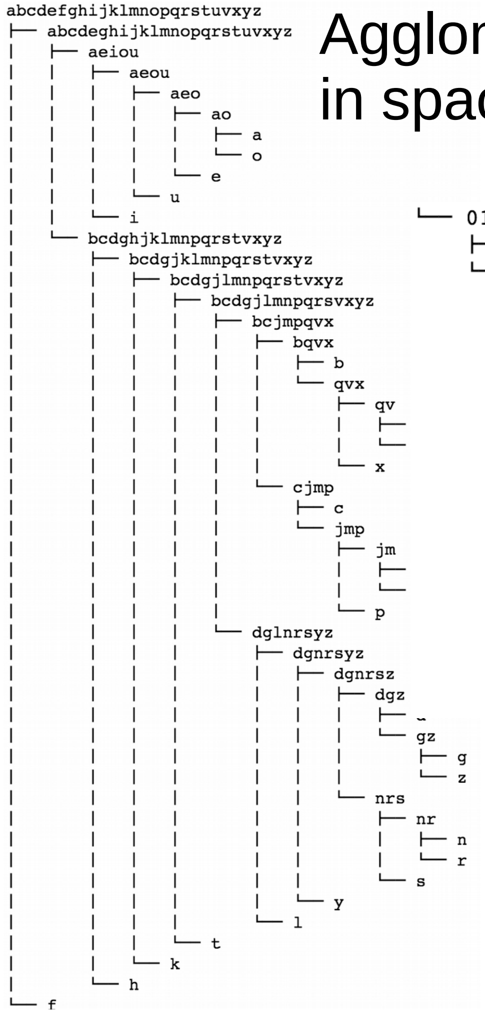
Results – Freedom-based Tokenization against Lexicon

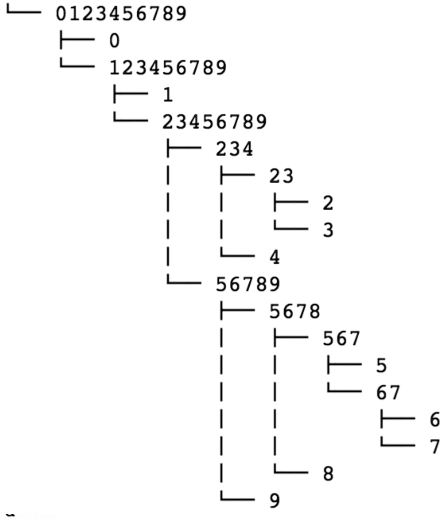
Language	Tokenizer	Tokenization F1	Lexicon Discovery Precision
English	Freedom-based	**0.99**	**0.99** (vs 1.0)
English	Lexicon-based	0.99	-
English no spaces	Freedom-based	0.42	-
English no spaces	Lexicon-based	0.79	-
Russian	Freedom-based	**1.0**	**1.0** (vs 1.0)
Russian	Lexicon-based	0.94	-
Russian 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	-

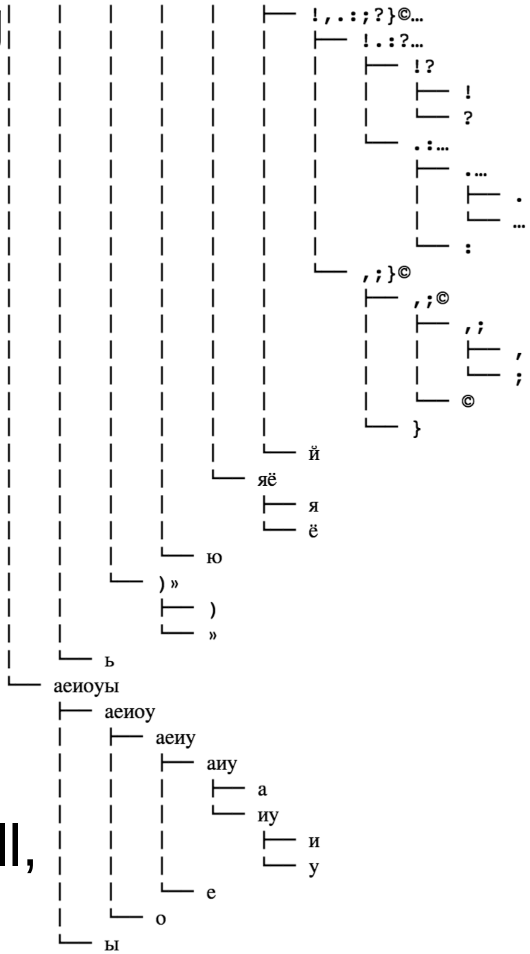
Lexicon-based Tokenization - greedy/beam search on word length (optimal) or frequency

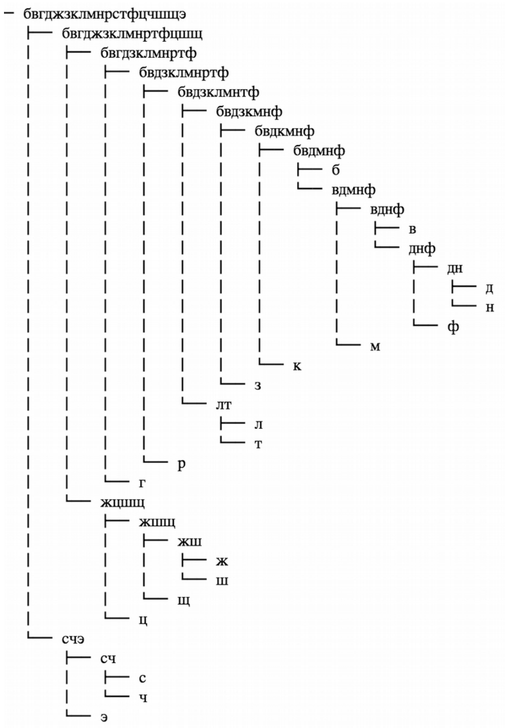
Unsupervised Character Category Learning

Agglomerative Clustering in space of Transitions





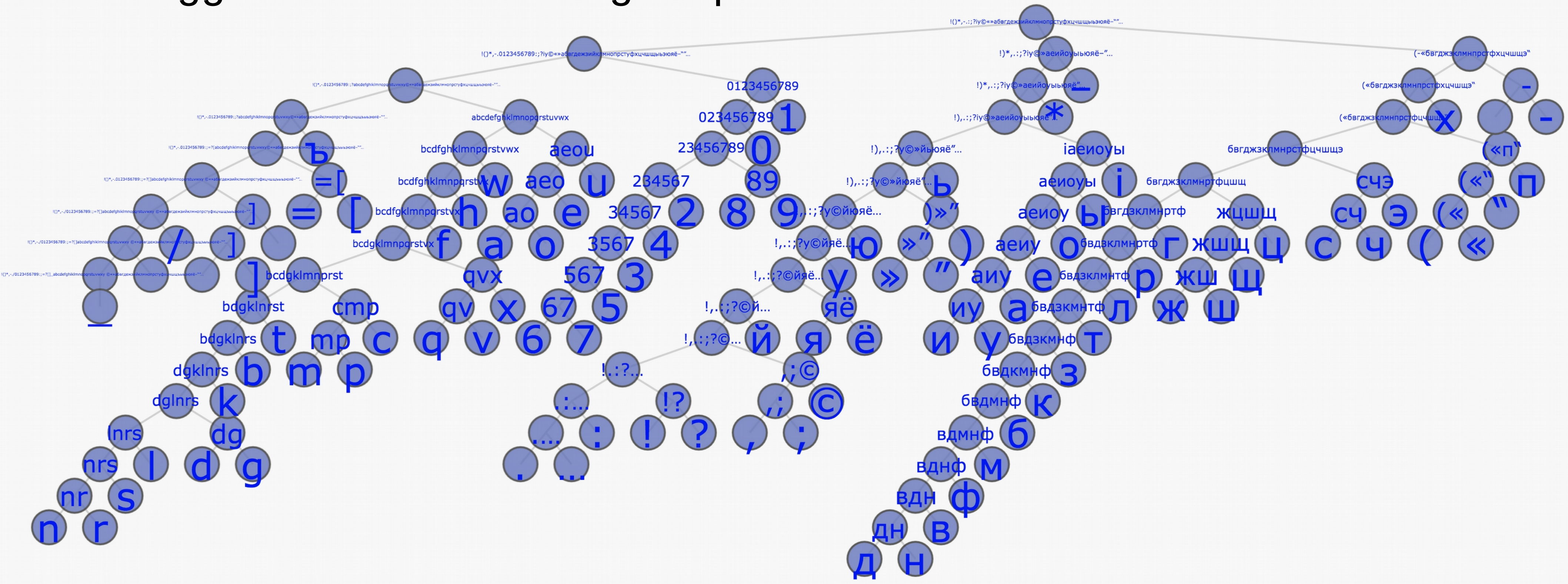




RusAge Test/Small, Cosine Similarity

Unsupervised Character Category Learning

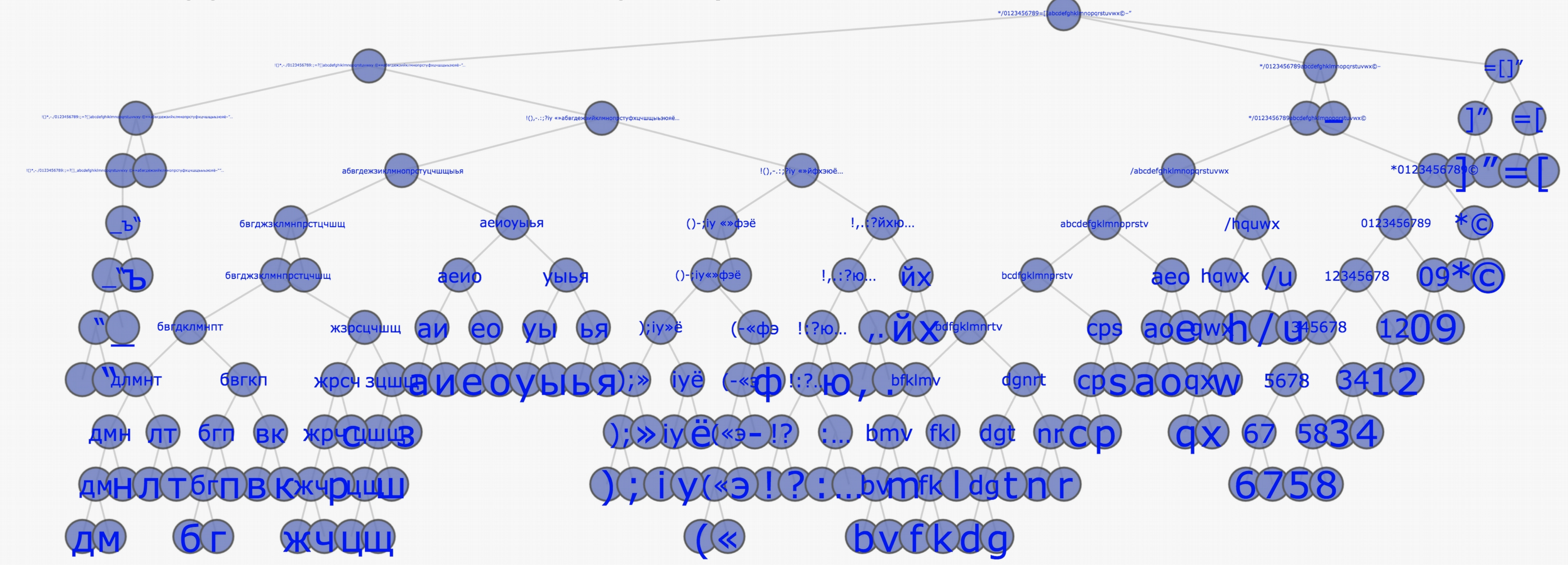
Agglomerative Clustering in space of Transitions



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.

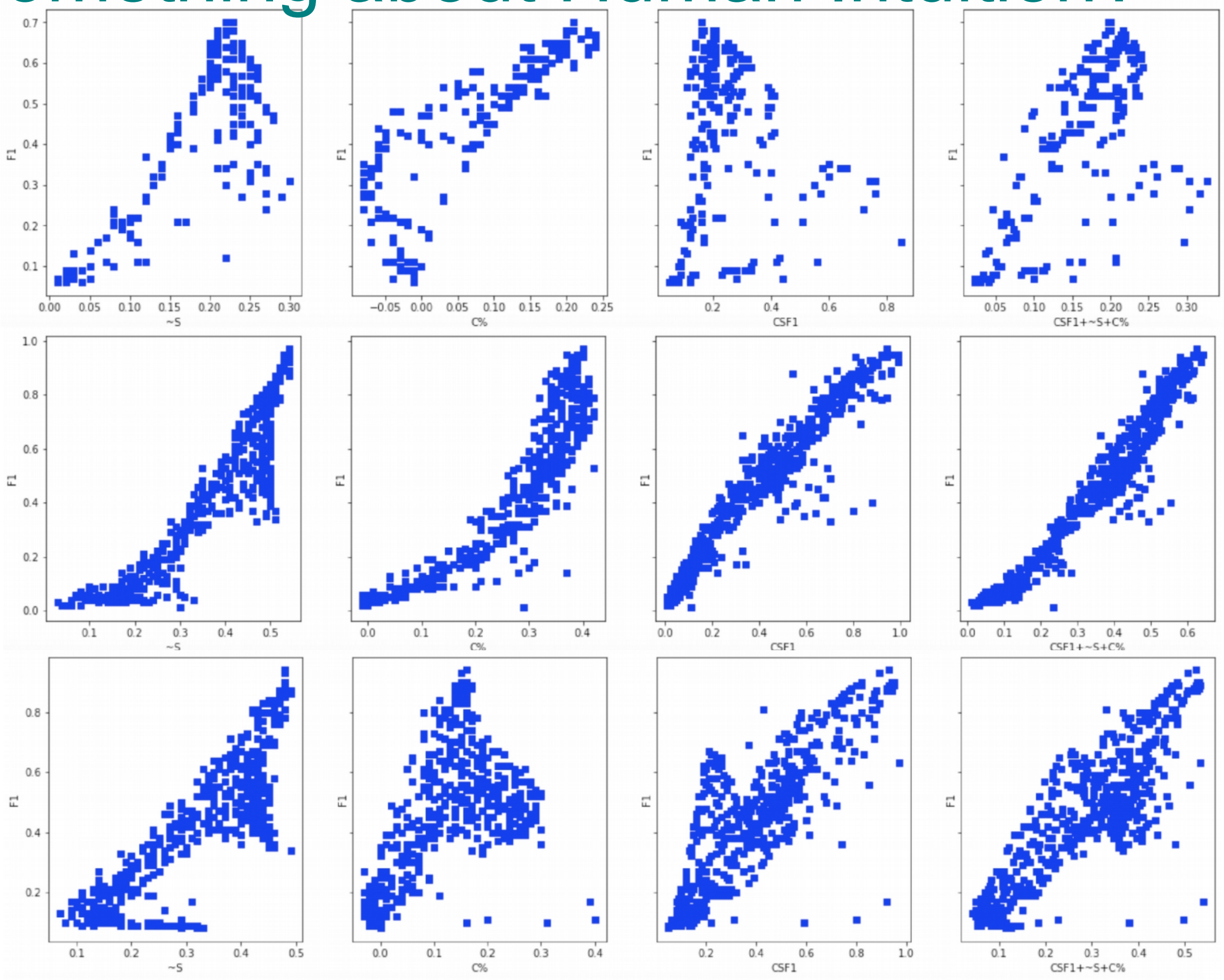
https://arxiv.org/abs/2205.11443
https://github.com/aigents/pygents

Something about Human Intuition?

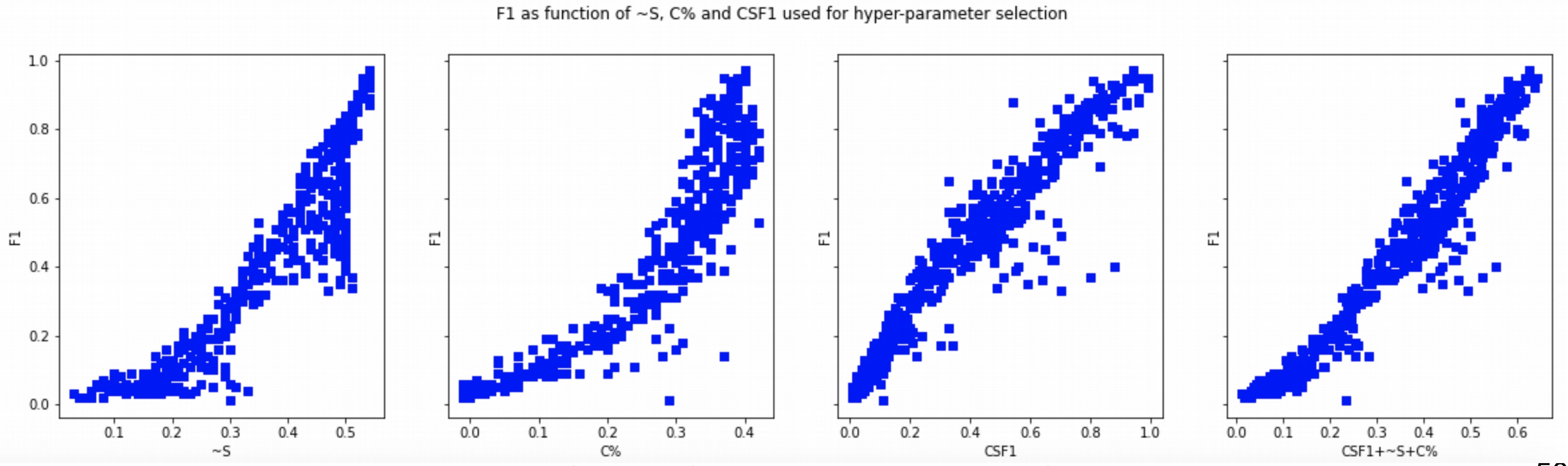
Language 1

Language 2

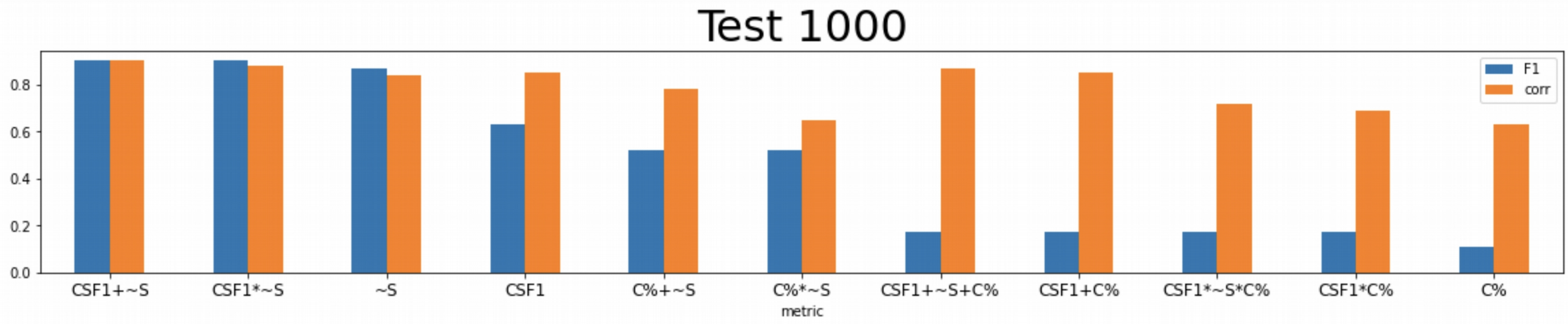
Language 3

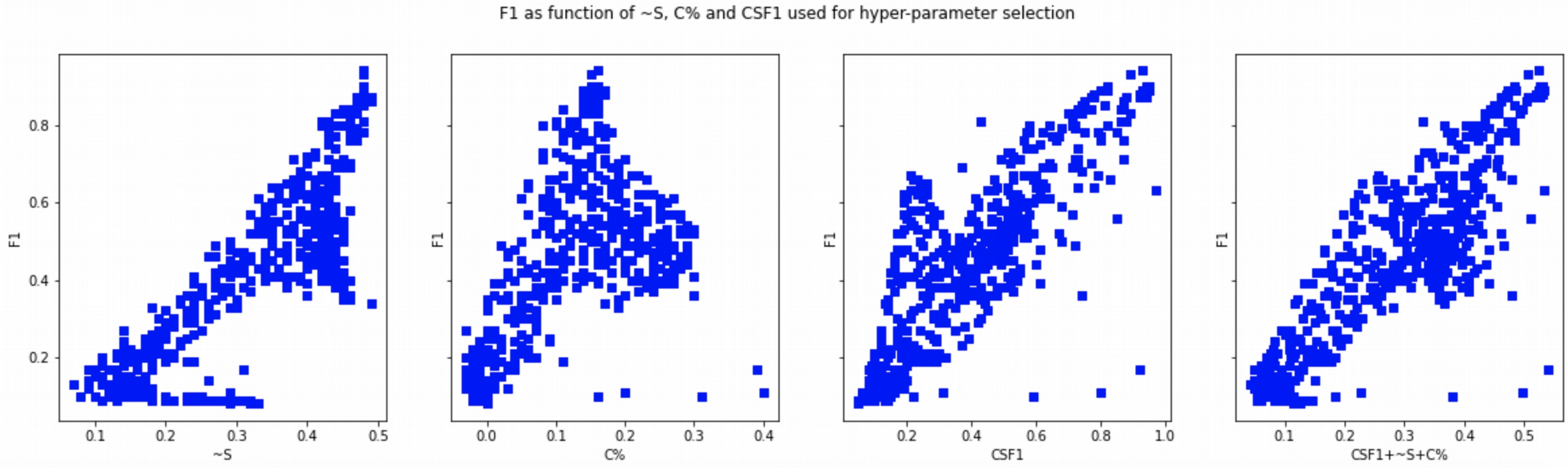


Self-tuning Hyperparameters – English (TF variance)

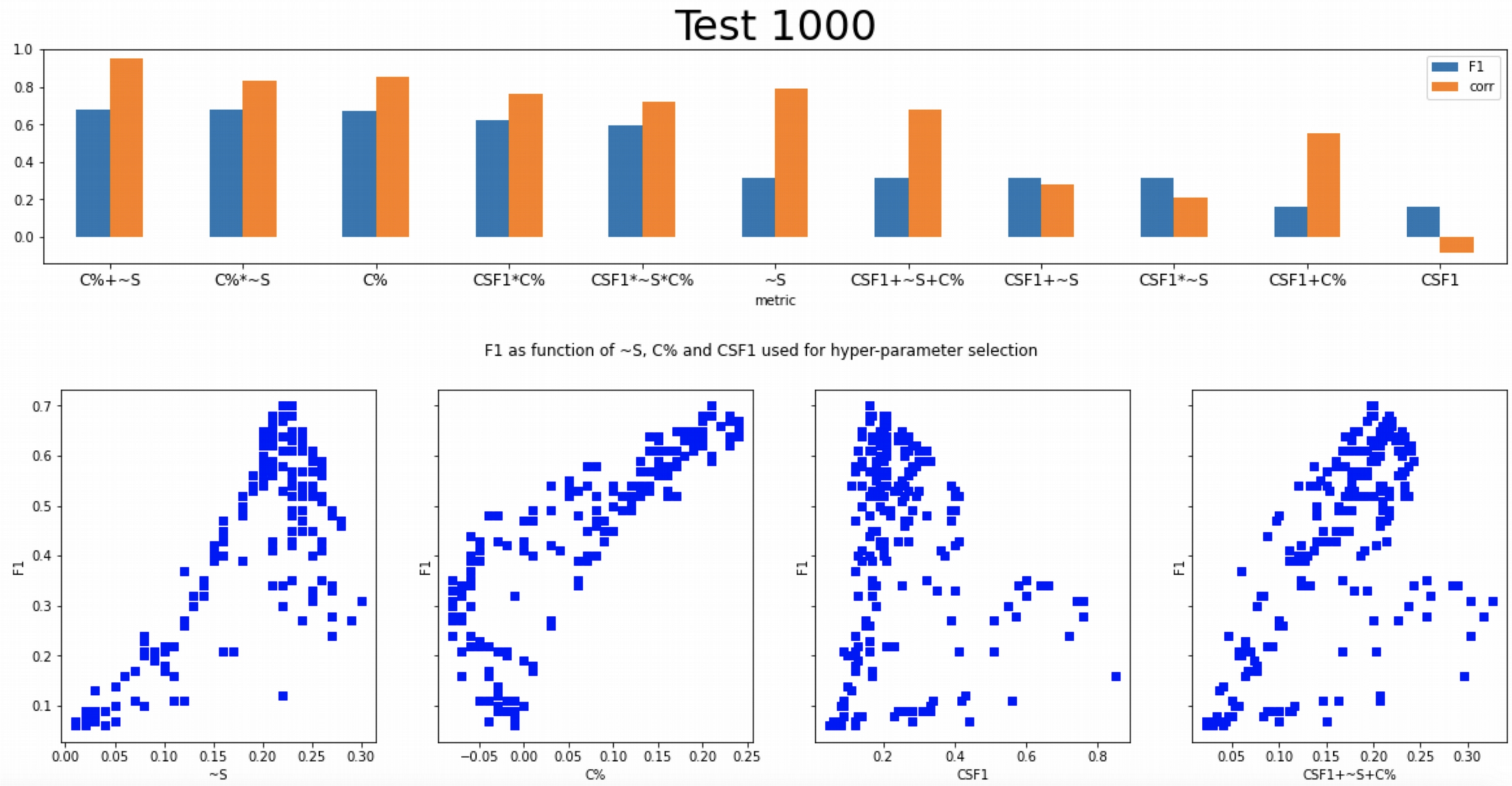


Self-tuning Hyperparameters – Russian (TF variance)

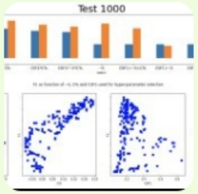




Self-tuning Hyperparameters – Chinese (TF “peak”)



Something about Human Intuition!



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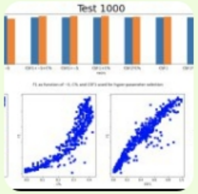
247.8 KB

OPEN WITH

Language 1

11:22



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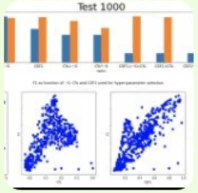
Language 2

11:23



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OPEN WITH

Language 3

11:23

Poll

11% 1 - Russian

23% 2 - Russian

70% 3 - Russian

5% 1 - English

70% 2 - English

17% 3 - English

82% 1 - Chinese

0% 2 - Chinese

5% 3 - Chinese

VIEW RESULTS

3 11:25

Thank You and Welcome!

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