TOWARDS A GENERAL FRAMEWORK FOR HUMOR GENERATION FROM RATED EXAMPLES

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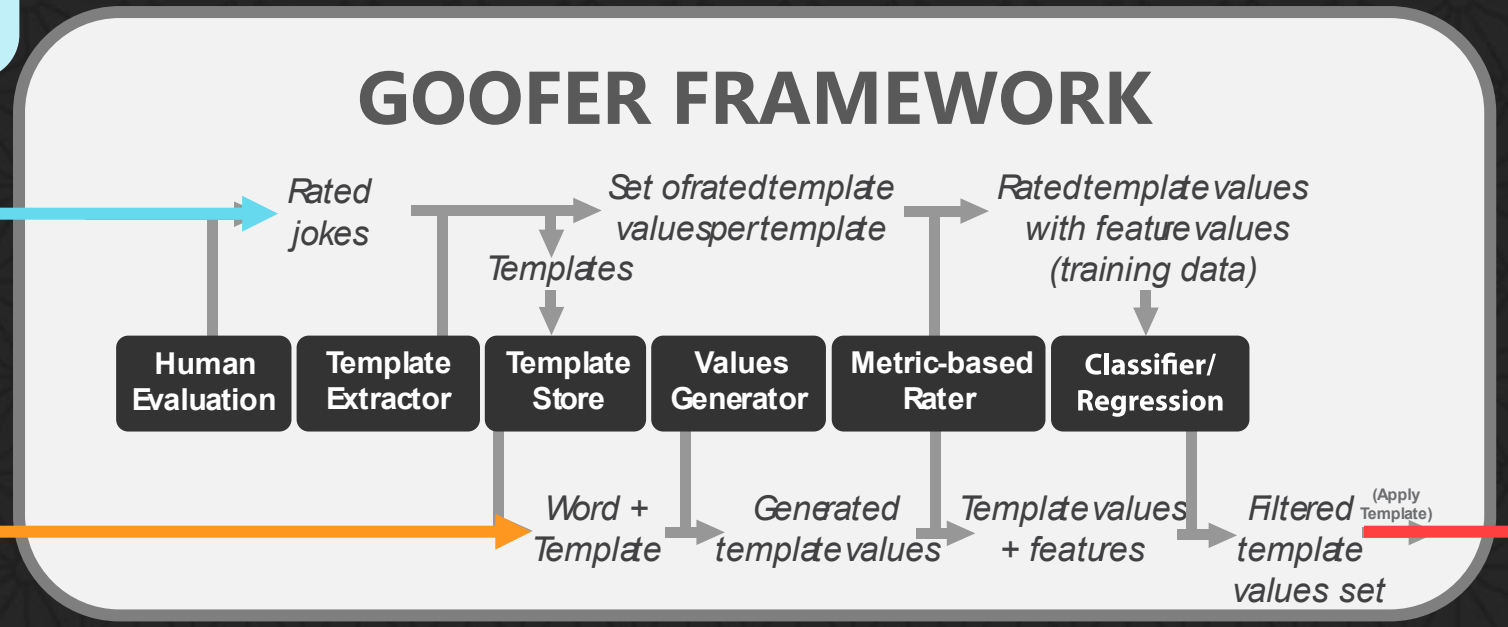
GENERATING JOKES FROM RATED EXAMPLES

corpus of
INPUT JOKES



SEED WORD
for joke

NEW JOKES
about seed word, in style of input jokes, of good quality

INCONGRUITY RESOLUTION THEORY

Setup	Two fish are in a tank. Says one to the other:
Punchline	“Do you know how to drive this thing?”

Obvious Interpretation



Hidden Interpretation

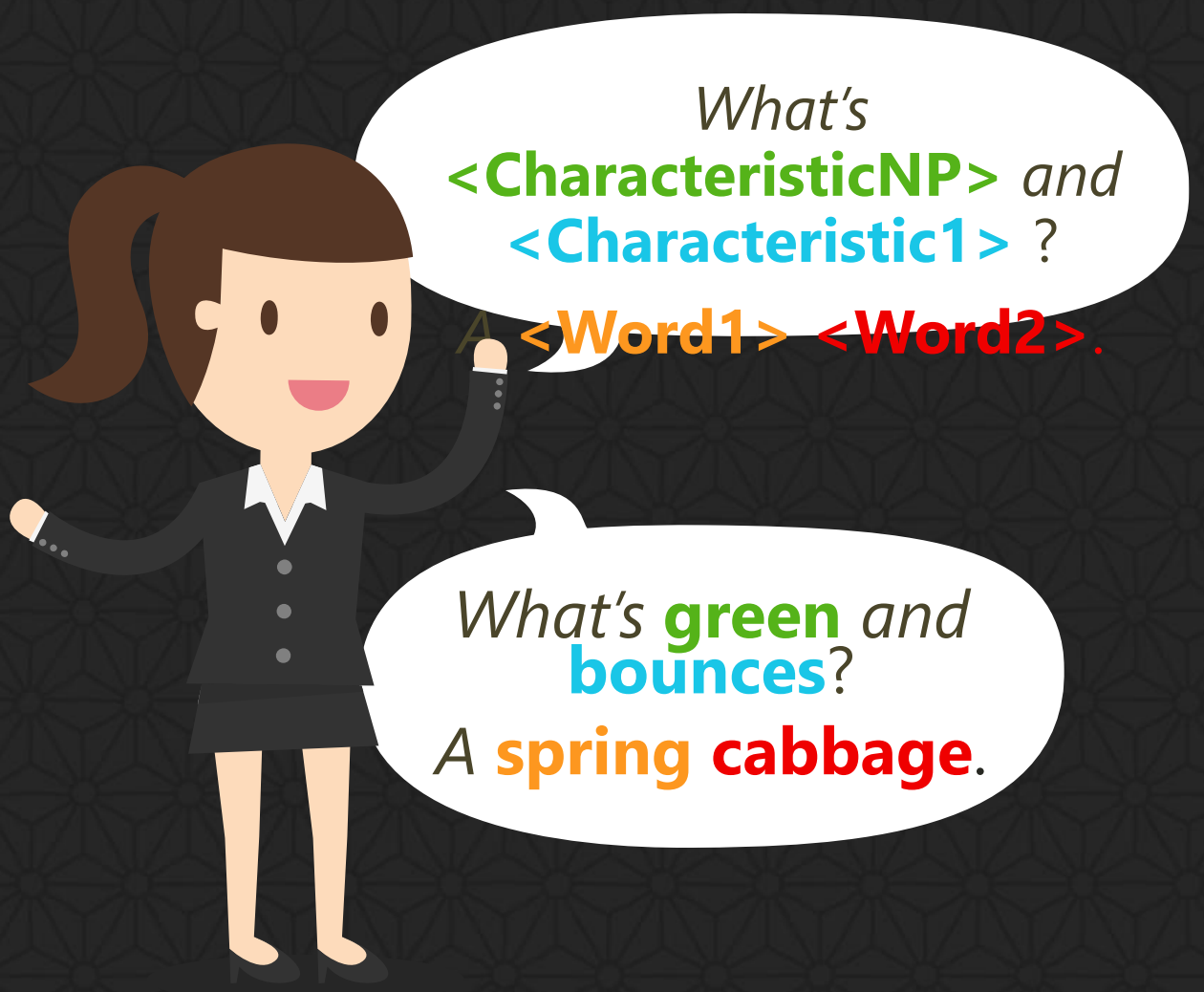


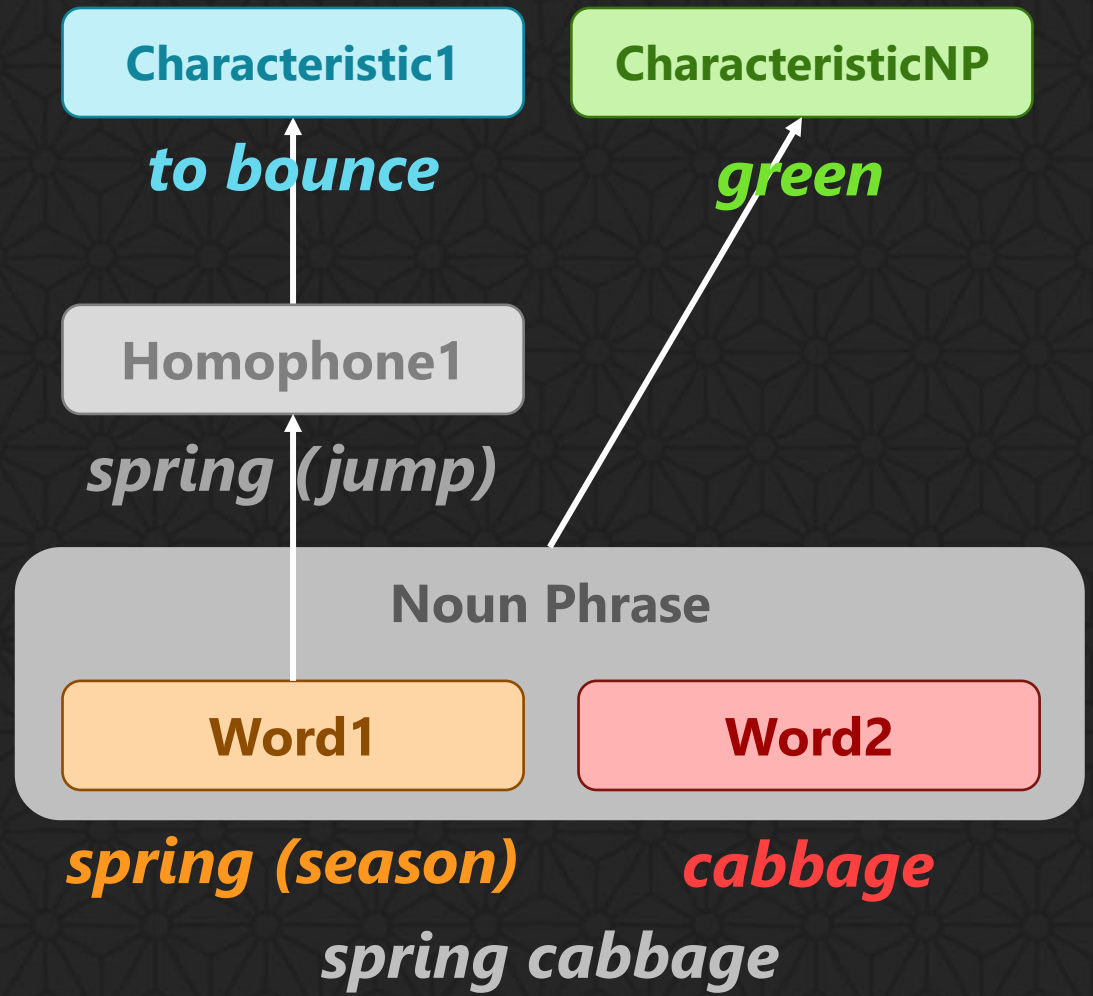
- Obviousness
- Comparison
- Inappropriateness

- Conflict — *Starts search process*
- Compatibility — *Stop condition*

Based on: Ritchie, G. (1999). Developing the incongruity-resolution theory.

JAPE & STANDUP: TEMPLATES AND SCHEMAS

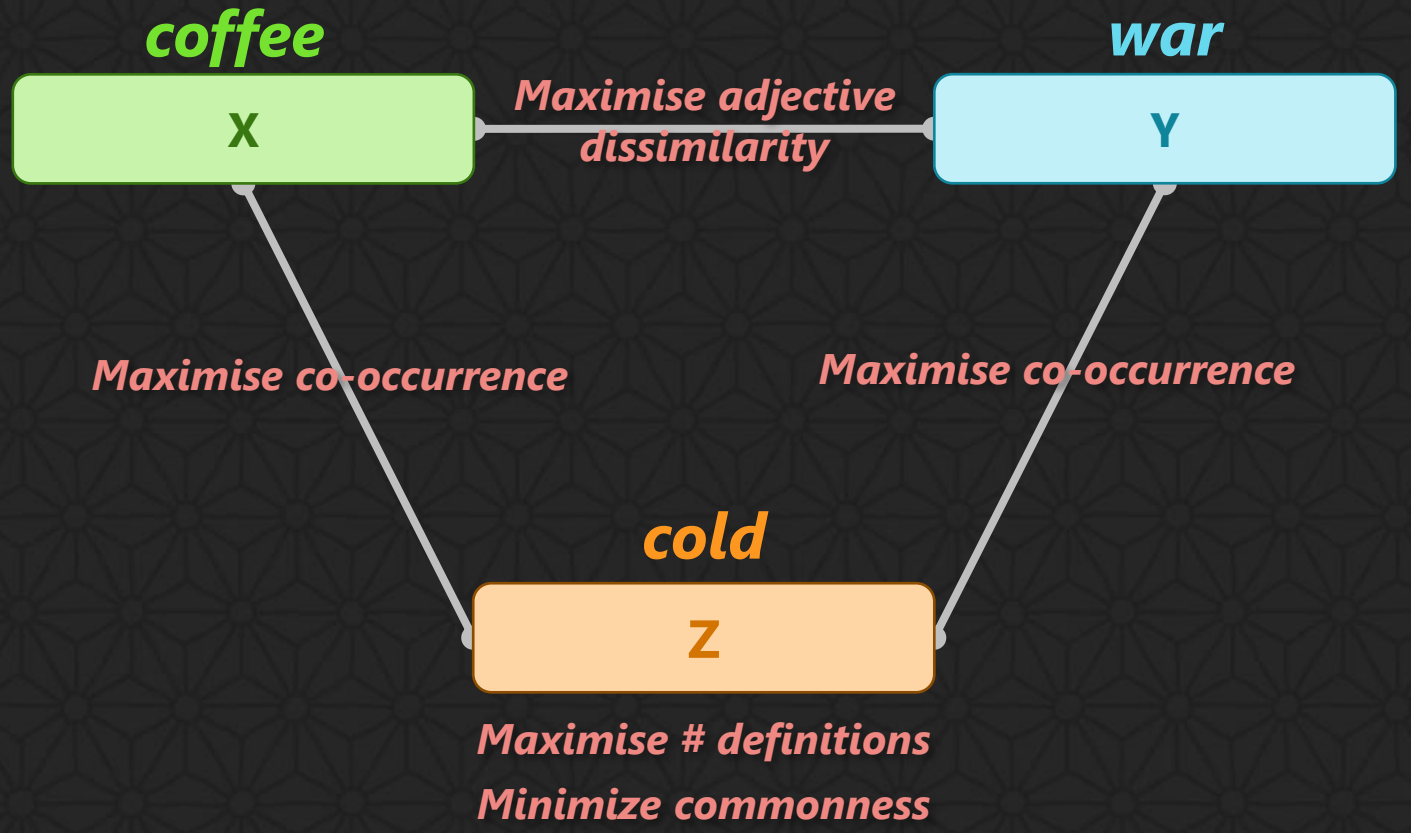




Binsted, K., & Ritchie, G. (1994). An implemented model of punning riddles. In proceedings of AAAI-94.
Ritchie, G., Manurung, R., Pain, H., Waller, A., & O'Mara, D. (2006). The standup interactive riddle-builder. IEEE Intelligent Systems, 21(2), 67-69.
Manurung, R., Ritchie, G., Pain, H., Waller, A., O'Mara, D., & Black, R. (2008). The construction of a pun generator for language skills development. Applied Artificial Intelligence,

UNSUPERVISED ANALOGY GENERATOR





Petrović, S., & Matthews, D. (2013). Unsupervised joke generation from big data. In Proceedings of the 51st Annual Meeting of the Association for Computational Linguistics

T-PEG

Generates punning riddles from examples using linguistic relations

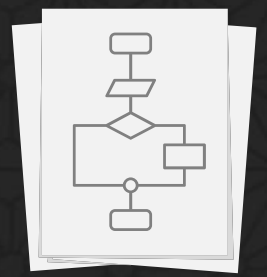
What part of a fish weighs the most? The scales.

→

What part of a **X** **Y** the most? The **Z**.

+

STANDUP-like schema



```
Z PartOf X
Z CapableOf Y
...
```

→

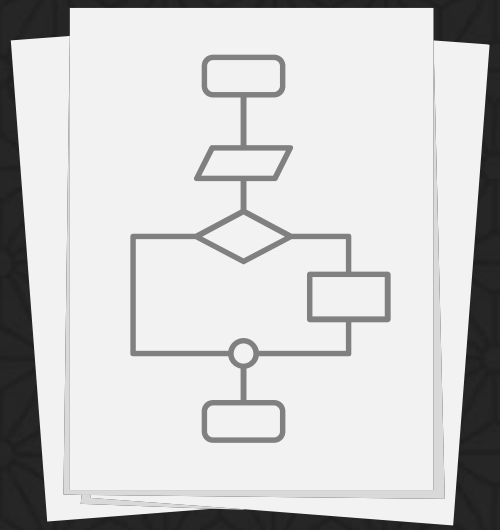
What part of a man lengthens the most? The shadow.

Human-created joke

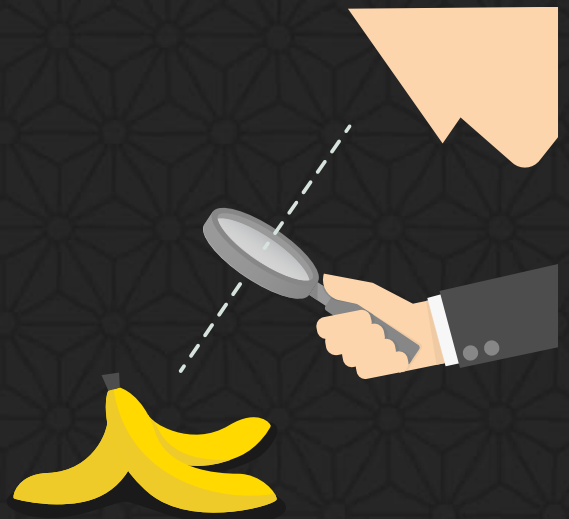
Generated joke

B. A. Hong and E. Ong,. (2008). Generating Punning Riddles from Examples. Second International Symposium on Universal Communication, Osaka, pp. 347-352.

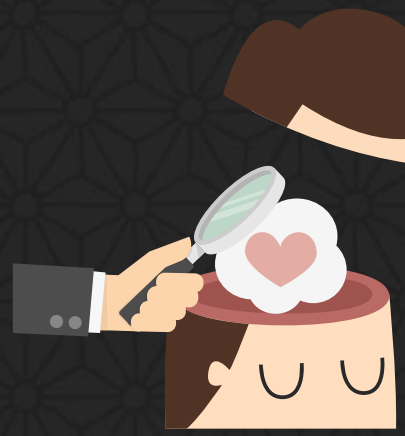
ISSUES IN STATE OF THE ART



“HARDCODED” TEMPLATES & SCHEMAS



NO FEEDBACK LOOP POSSIBLE



Individual Dimension

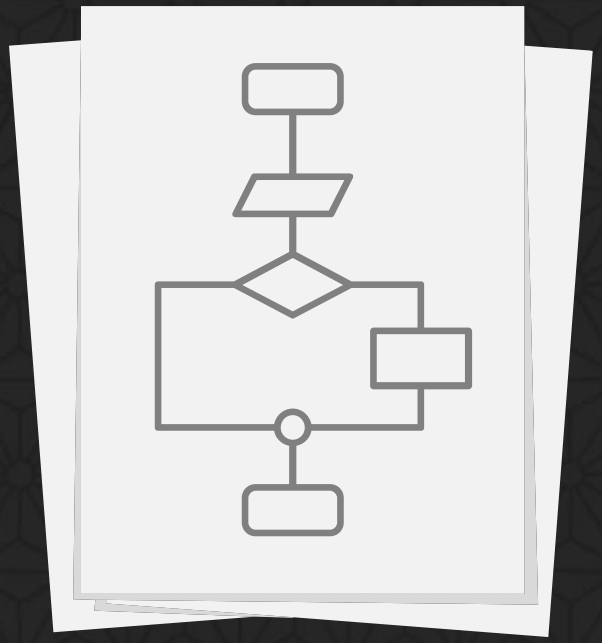
Temporal Dimension



GOOFER FRAMEWORK

Generator of One-liners from Examples with Ratings

METRICAL SCHEMA



Header

Keywords

Template

Features





Aggregator

Values Generator



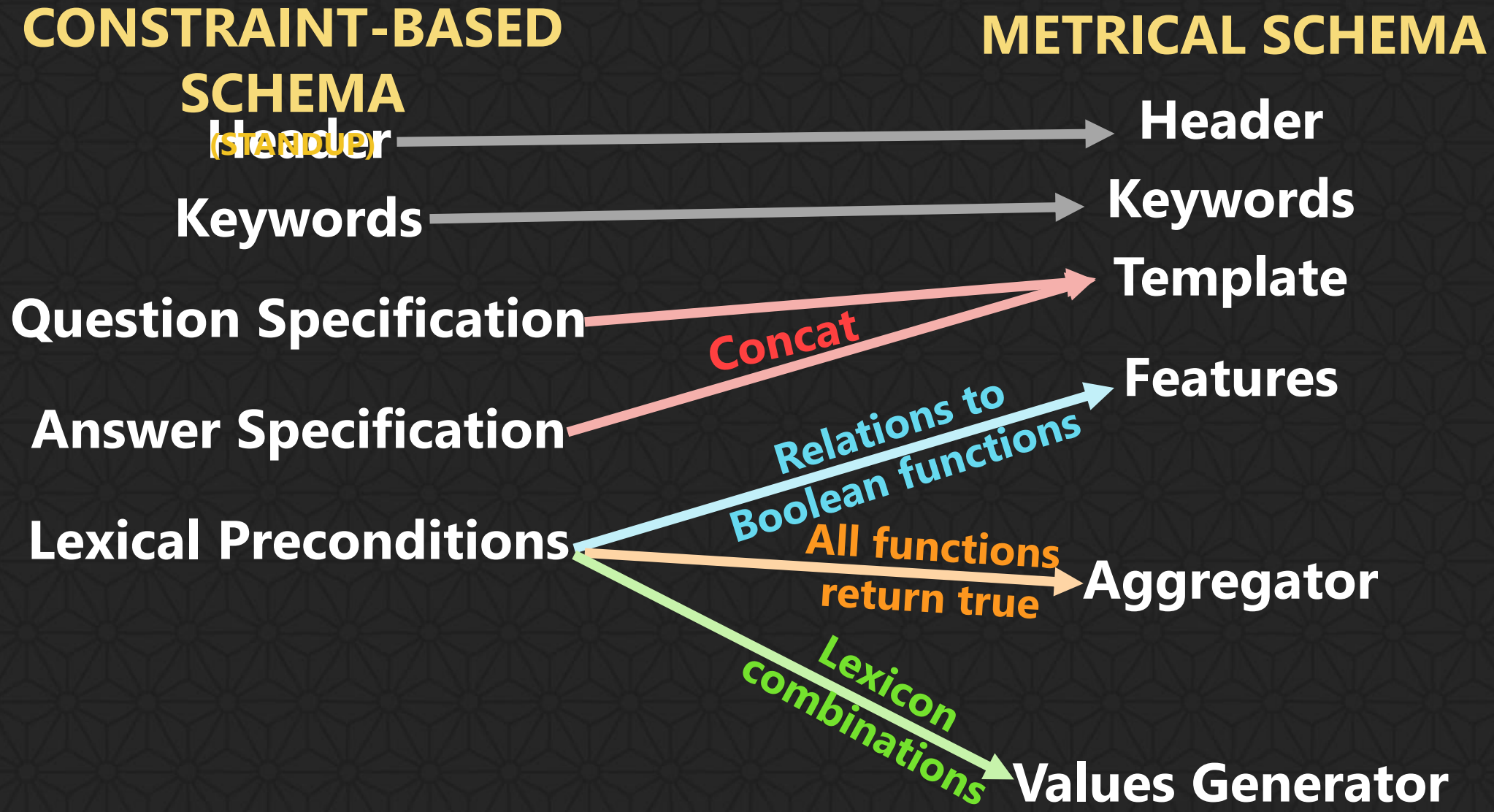
Constraint-based Schemas

Hard to tweak to preference

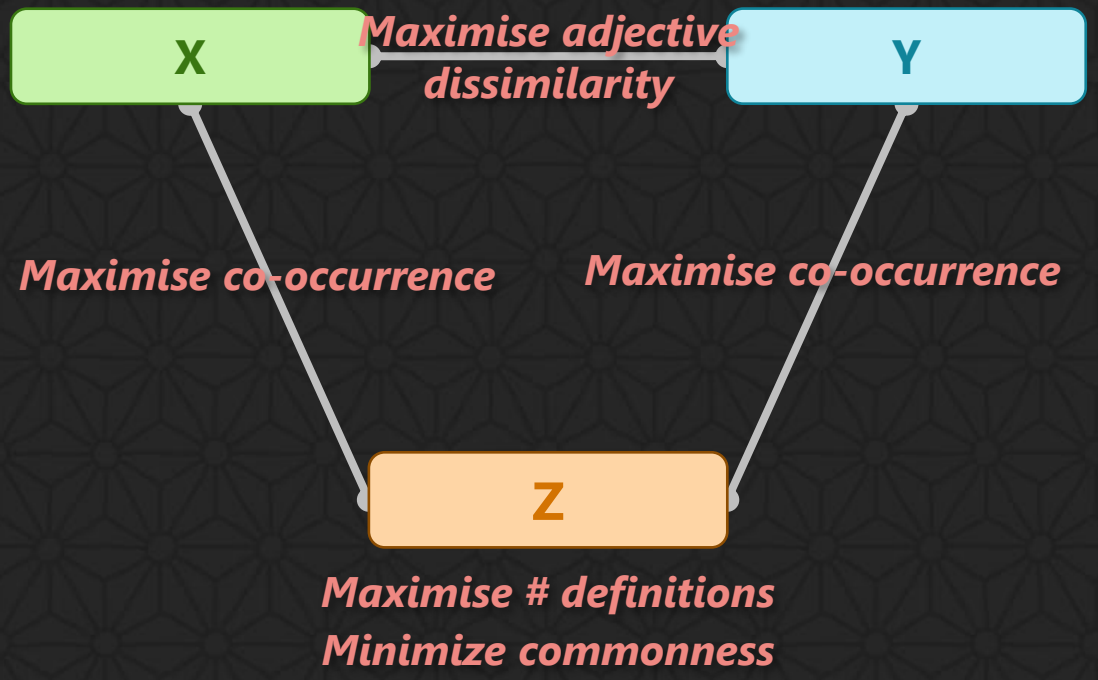
Proposal: Metrical Schema

Allows for learning in aggregator component

PROOF OF SCHEMA GENERALISATION



MAPPING ANALOGY GENERATOR TO SCHEMA APPROACH



HEADER: `pm_analogy_model(X, Y, Z)`

KEYWORDS: [X, Y, Z]

TEMPLATE: I like my X like I like my Y, Z

FEATURES: `relatedness(X, Z), relatedness(Y, Z), dissimilarity(X,Z), ambiguity(Z), uncommonness(Z)`

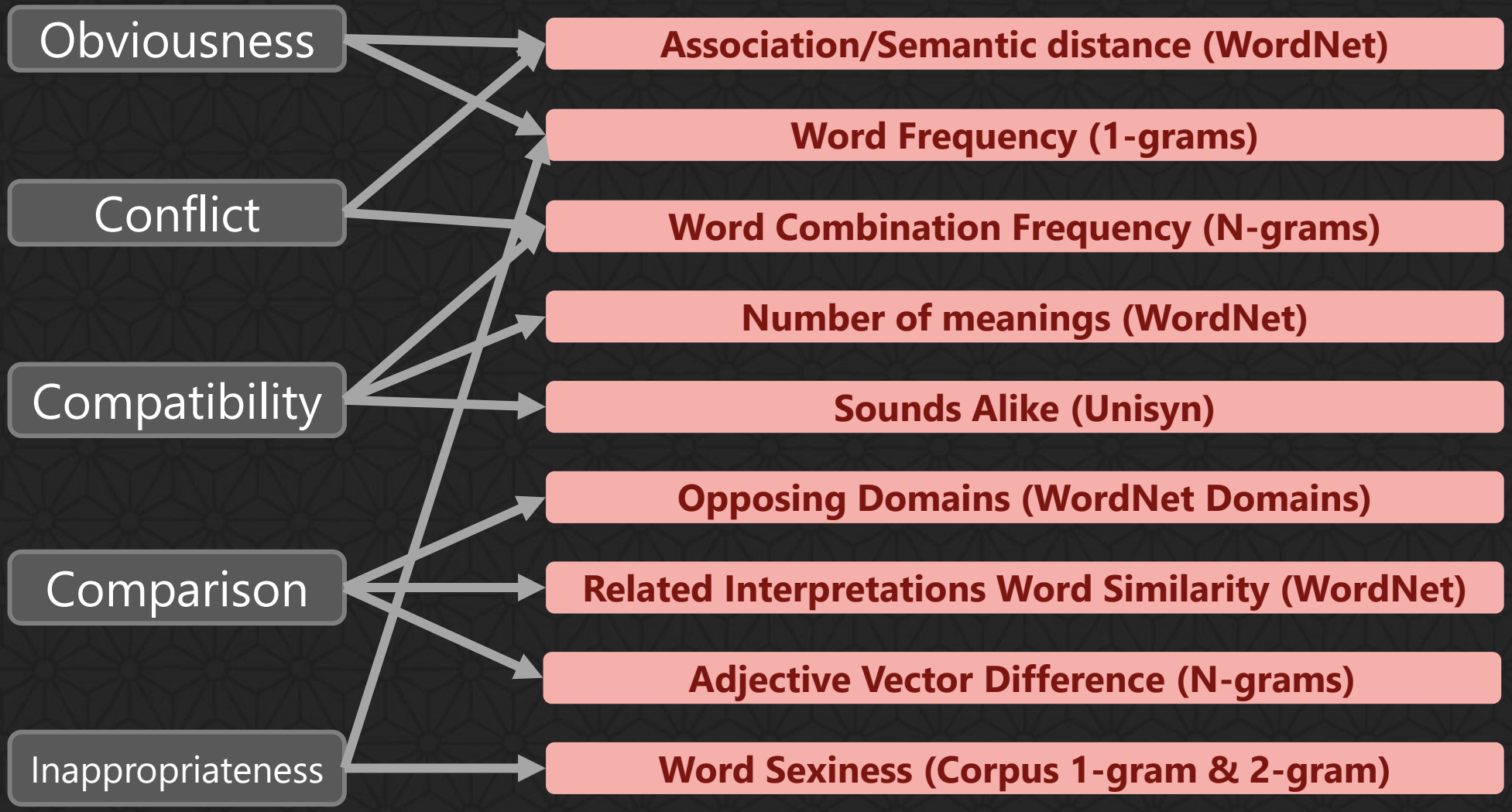
AGGREGATOR: Product of features below threshold *t*

VALUES GENERATOR:

1. Take X from input
2. Generate Z from X as possible adjective used with X *(n-gram)*
3. Generate Y from Z as possible noun used after Z *(n-gram)*

METRICS SET IDENTIFICATION

By approximating Incongruity Resolution theory parameters



GOOFER FLOW

a) I like my relations l
b) I like my coffee like
c) The sailor bears a s
d) I like my girlfriend
e) The lord cultivates

Joke	Rater 1	Rater 2	Rater 3
a	5	4	5
b	4	4	3
c	5	3	4
d	2	1	3
e	3	2	2

Template 1: "I like my X like I like my Y, Z."
relations, source, open | [5,4,5]
coffee, war, cold | [4,4,3]
girlfriend, estate, real | [2,1,3]

Template 2: ``The A B a C. D.''
sailor, bears, stress, Pier pressure | [5,3,4]
lord, cultivates, region, A baron land | [3,2

X	Y	Z	Score	FreqX	FreqY	FreqZ	FreqXY
relations	source	open	[5,4,5]	3 831 210	4 050 904	4884757	0
coffee	war	cold	[4,4,3]	784 065	9 211 826	2 010 173	0
girlfriend	estate	real	[2,1,3]	75 392	998 669	5 284 057	0

1. **Training** → *Input Jokes* → *Rated Jokes* → *Set of rated template values per template* → *Rated template values with feature values (training data)*

Templates

Human Evaluation | **Template Extractor** | **Template Store** | **Values Generator** | **Metric-based Rater** | **Classifier/ Regression**

2. **Generating** → *Seed word* → *Word + Template* → *Generated template values* → *Template values + features* → *Filtered template values set* → **(Apply Template)** → *Jokes about seed*

"Men"

"Men" + *"I like my X like I like my Y, Z."*

a) men, grave, nameless
b) men, country, cold
c) men, rain, gentle
d) men, laugh, silly
e)

X	Y	Z	Score	FreqX	FreqY	FreqZ	FreqXY	...
men	grave	nameless	?	9 876 543	4 050 904	4884757	0	...
men	country	cold	?	9 876 543	9 211 826	~~2 010 173~~	~~0~~	~~...~~
men	turkey	roast	?	9 876 543	998 669	~~5 284 057~~	~~0~~	~~....~~
men	rain	gentle	?	9 876	9 876	845 321	0	

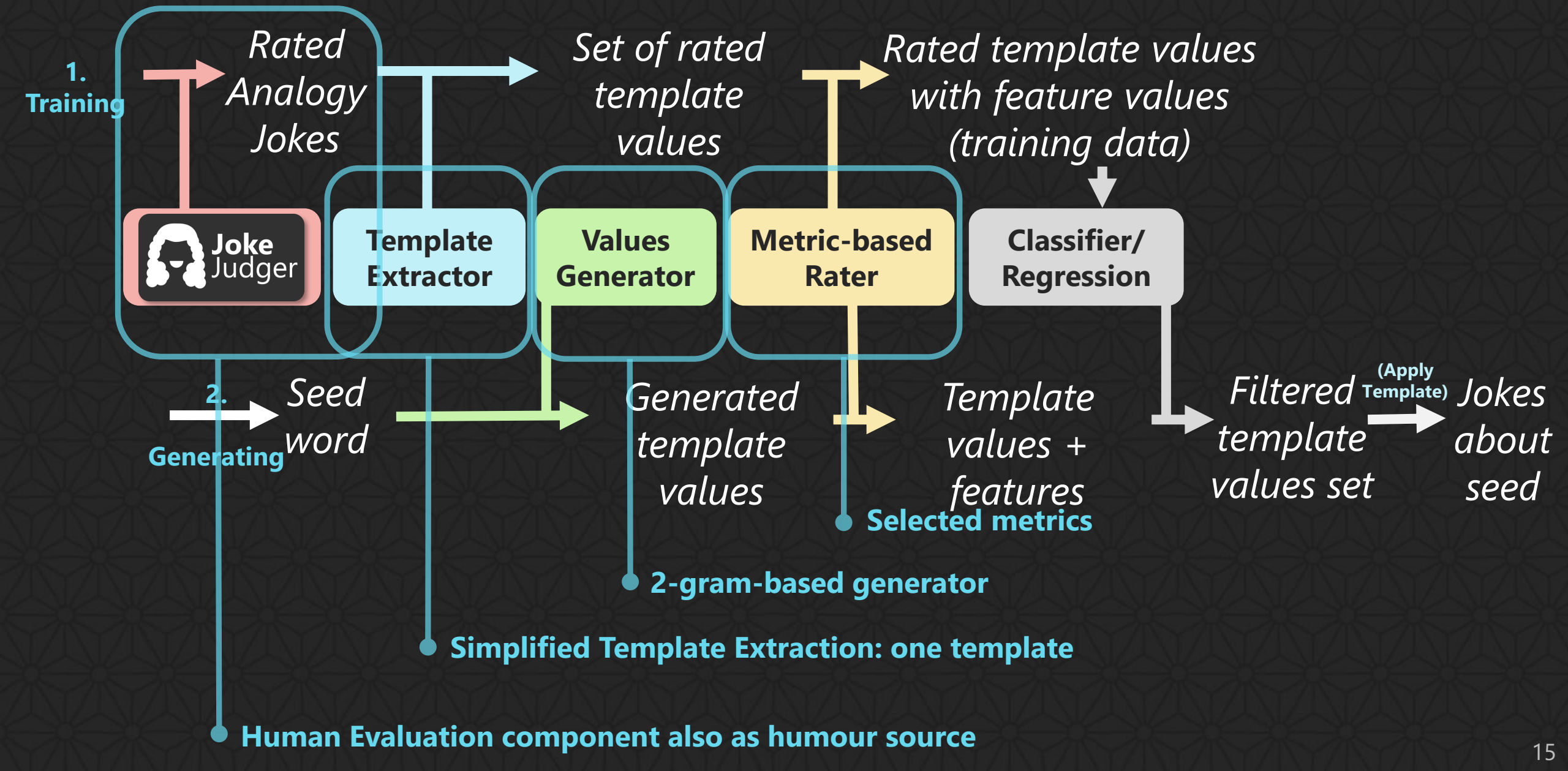
men, grave, nameless => 5
men, I like my men like I like my grave: namele
men, rain, gentle => 4
men, laugh, silly => 1
men, rain, gentle => 1

EVALUATION: GAG

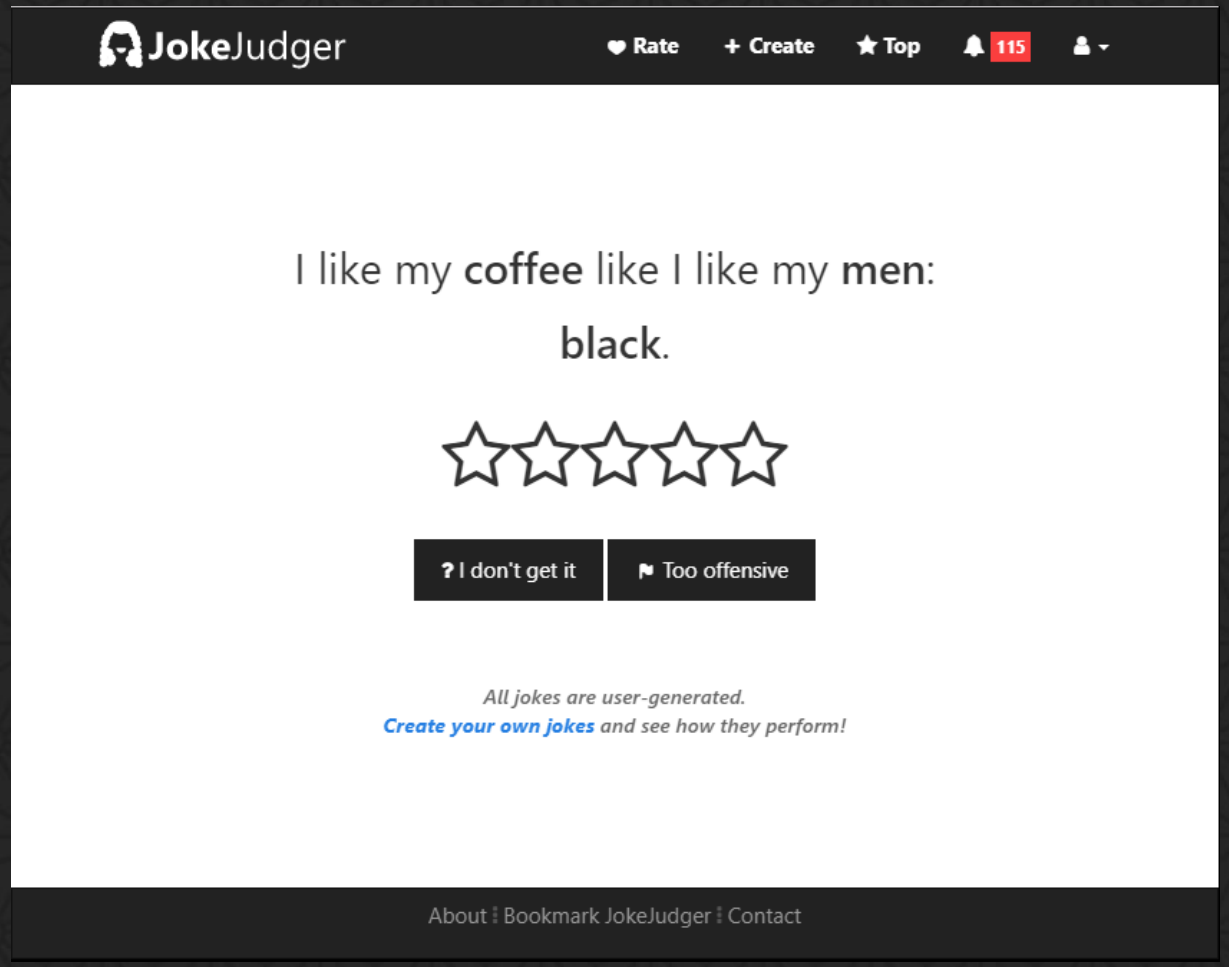
GENERALISED ANALOGY GENERATOR

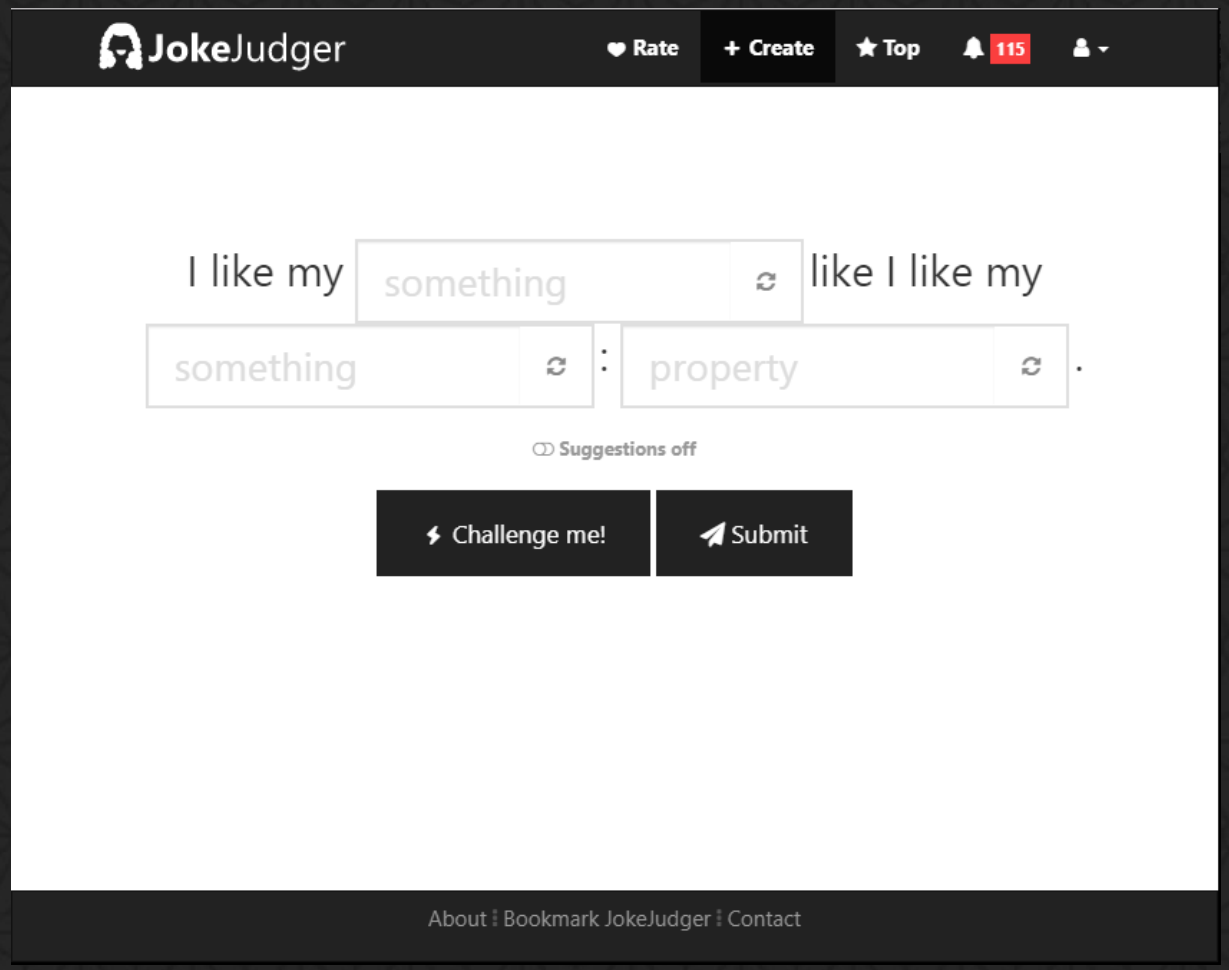
As done in our previous research: Winters, T., Nys, V., & De Schreye, D. (2018, July). Automatic joke generation: Learning humor from examples. In International Conference on Distributed, Ambient, and Pervasive Interactions (pp. 360-377). Springer, Cham.

GOOFER SIMPLIFICATIONS: GAG



JOKEJUDGER





Code: https://github.com/twinters/jokejudger

JOKEJUDGER: COLLECTED DATA



203 users



9034 ratings
418 markings



424 human jokes
100 generated jokes



41,9% average agreement on most frequent rating

Data available on https://github.com/twinters/jokejudger-data

CLASSIFICATION & REGRESSION





CLASSIFICATION

most frequent rating



5 star jokes
= Small number & High variety
→ **HARD TO PREDICT**

Trained Random Forest:
61.5% correctly classified

REGRESSION

average rating

HUMOUR APPRECIATION VARIES A LOT

→ Average score close to centre

Random Forest: RRSE 84%

GENERATED VS HUMAN CREATED JOKE EXAMPLES

I like my **coffee** like I like my **sleep**: **strong**.

I like my **men** like I like my **graves**: **nameless**.

I like my **women** like I like my **tests**: **independent**.

I like my **women** like I like my **bills**: **remaining**.

I like my **men** like I like my **society**: **heartless**.

I like my **men** like I like my **rain**: **gentle**.

I like my **computer** like I like my **affection**: **personal**.

GAG
GENERALISED
ANALOGY
GENERATOR

I like my **chess climaxes** like I like my **Australian dinners**: **check, mate**.

I like my **chickens** like I like my **eggs**: **suspended in a state of philosophical inquiry**.

I like my **cat** like I like my **cat**: **I just really love cats**.

I like my **parties** like I like my **hospitals**: **mental**.

I like my **logic** like I like my **logic**: **circular and like my logic**.

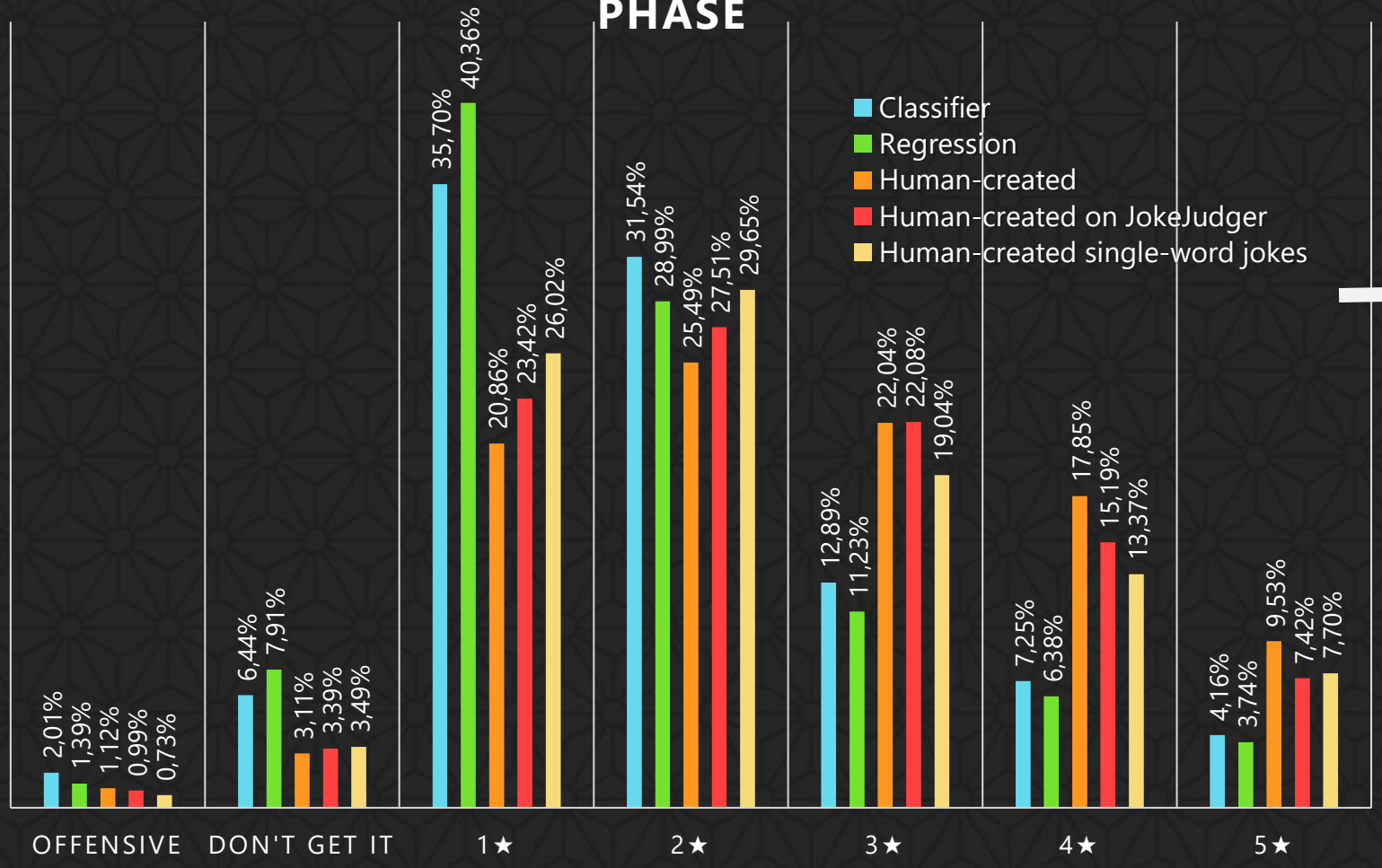
I like my **compliments** like I like my **jokes**: **I don't get them**.

I like my **partners** like I like my **play-doh**: **soft and moldable**.

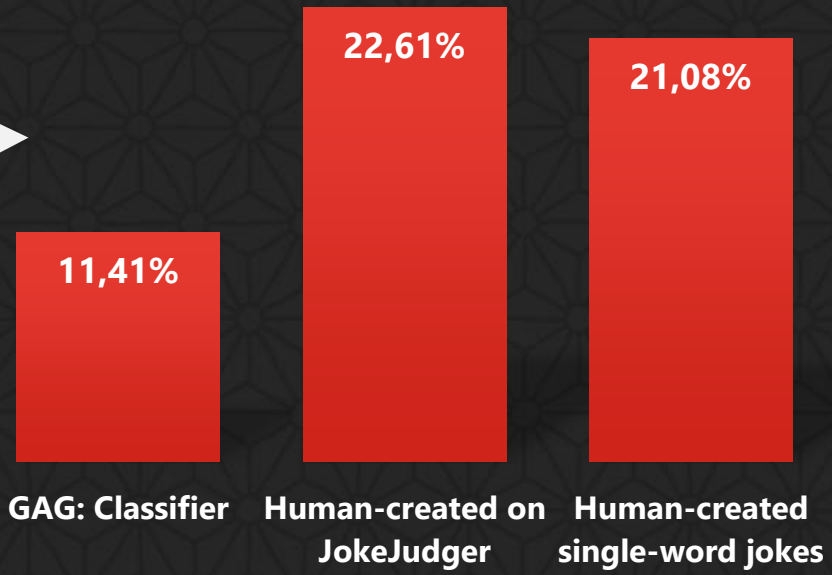


EVALUATION

RELATIVE NUMBER OF RATINGS PER RATING TYPE FOR DIFFERENT SOURCES AND CATEGORIES OF JOKES DURING EVALUATION PHASE



4+ RATINGS FREQUENCY



FUTURE WORK



General Template Extraction

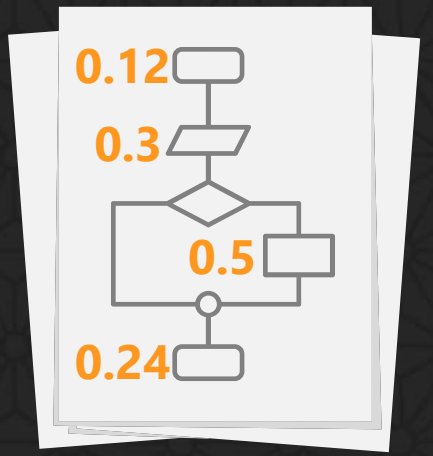
Multiple levels of granularity

Learn from large joke corpus

I like my **jokes** *like I like my* **convicts**: **having longer sentences**

Multiword Template Values

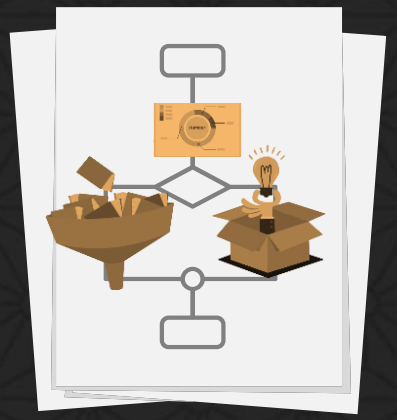
BERT? GPT-2?



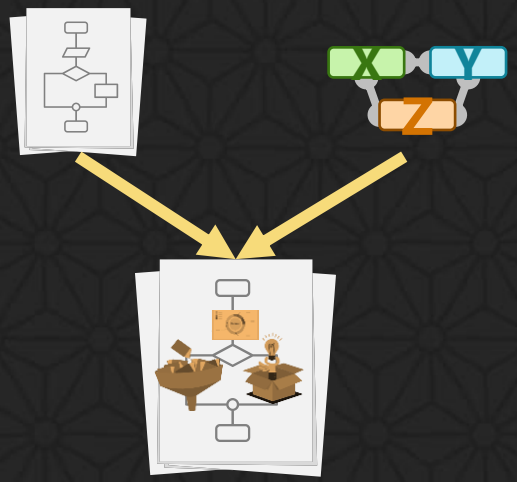
Probabilistic Schemas

Higher interpretability

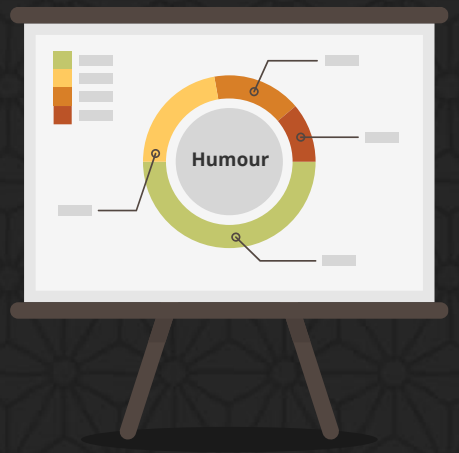
CONCLUSION



Proposed new **METRICAL SCHEMA**



Proved its **GENERALISATION**



Demonstrated **METRIC SET IDENTIFICATION**



Showed working with **MACHINE LEARNING**

Code available on https://github.com/twinters/goofer



Thank you!

Towards a General Framework for Humor Generation from Rated Examples

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@thomas_wint

Some images (based on the works) of dooder on freepik.com