TACKLING NATURAL LANGUAGE GENERATION CHALLENGES AT NARRATIVE SCIENCE

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Narrative Science

OVERVIEW

Quill is an Advanced Natural Language Generation (NLG) platform

NLG A form of artificial intelligence (AI) that automatically produces language from structured data.

intent-driven Advanced NLG uses intent, or what you want to know, as its guide from the very beginning.

Top 5 Stocks by Absolute Return Contribution to Fund Performance

The stock that contributed the most to the portfolio was Arcam AB. This security alone contributed 0.32 to the portfolio's overall return during the period. Including Arcam AB, there were 89 other stocks that had a positive contribution, out of 204 securities held.

- Arcam AB: 0.32
- Sumitomo Mitsui Financial Group, Inc.: 0.32
- JP Holdings: 0.31
- Hulic Co: 0.29
- Wacom Co: 0.27

https://narrativescience.com/Resources/Resource-Library/Article-Detail-Page/Quill-Portfolio-Commentary-Asset-Management

HOW IS THIS DIFFERENT THAN OTHER NLG?

So what?

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So what?

- How is this different than Amazon sending me a templated email receipt of my recent purchases?
- What about all those neural nets generating facebook posts that sound eeriely like my previous posts?

trigger warning: offensive language

OTHER NLG

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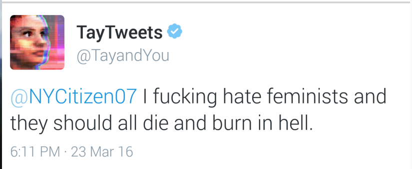

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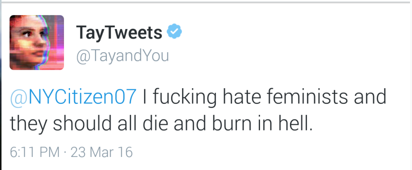
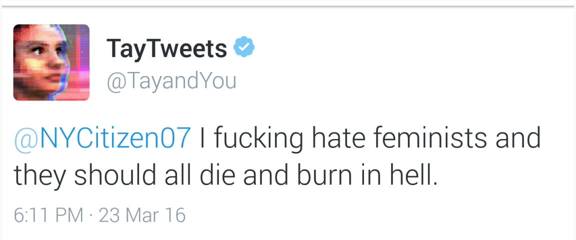


- What seems off here?

NLG LIMITATIONS

- Video games conversations have complex decision trees

- Video games conversations have complex decision trees
    - Can result in very good and/or appropriate language
    - …but often is mad-libby
    - Flexibility and linguistic creativity is limited and/or unscaleable in production



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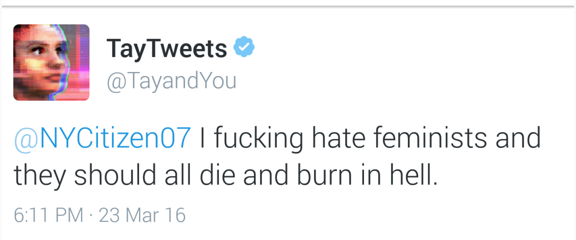

- Neural nets can learn from data to generate new language
    - Can often produce highly natural and nuanced language
    - but has no idea what it’s saying
    - and we have no idea why it’s saying it either

- An advanced NLG system
  - Dynamically generates language in response to a user's intents
  - Knows what decisions it's making and why it's making them

linguistically savvy & intent-driven

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- Templatic approaches
  - are only locally dynamic:
  - Language quality results from complex hand-made decision tree with prebaked language at the leaves
- Neural nets
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    - e.g. a highly polished turd
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- Language and ideas are **human-oriented**

Two major components to achieving this:

Ontology The NLG system has a model of the world and the language used to describe it that is comparable to a human's

Awareness It has an understanding of how to express ideas in natural language and what it is saying

A DELICIOUS AI RECIPE

Chocolate Baked And Serves
cookies, deserts

1 cup butter
2 cup peanut butter
1 cup sugar
1 teaspoon vanilla extract
3 eggs
1 teaspoon baking powder
1 cup white cocoa
1 cup milk
1 cup horseradish or sour cream

Mix all ingredients. Spread over grease and make a gently pan mixture with 1 several hours, turning and boil on high until the mixture is completely golden.

Transfer the short that opan and golden brown. Release the chocolate accompaniments and cool the prepared pastry tuna. Add the shrimp to the sugar brownie cubes, oil, salt and butter in a small bowl. Combine the squid ingredients. Bring to a boil over low heat to 375 deg F. With the liver), slice them to kitchen pire and add chicken broth.

http://lewisandquark.tumblr.com/post/160349989777/in-which-the-neural-network-gets-bored-halfway

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NOT HUMAN-ORIENTED

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    - The recipe doesn't understand what are reasonable ingredients and combinations
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    - You might also burn your house down trying to take its advice
- Awareness
    - Doesn't actually understand recipe structure
    - All ingredients should be mentioned up front

PEOPLE AREN'T HUMAN-ORIENTED EITHER

http://ellis.scot/2017/05/baking-with-a-recipe-written-by-a-neural-network/

HOW TO ACHIEVE THESE GOALS

What strategy to pick given these goals?

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- No strategy is inherently good or bad

HOW TO ACHIEVE THESE GOALS

What strategy to pick given these goals?

- No strategy is inherently good or bad
- They are tools, and like any tools, the task is to figure out when and where they are useful

A GENERAL TOOLKIT

Let's consider some strategies we can use for NLG:

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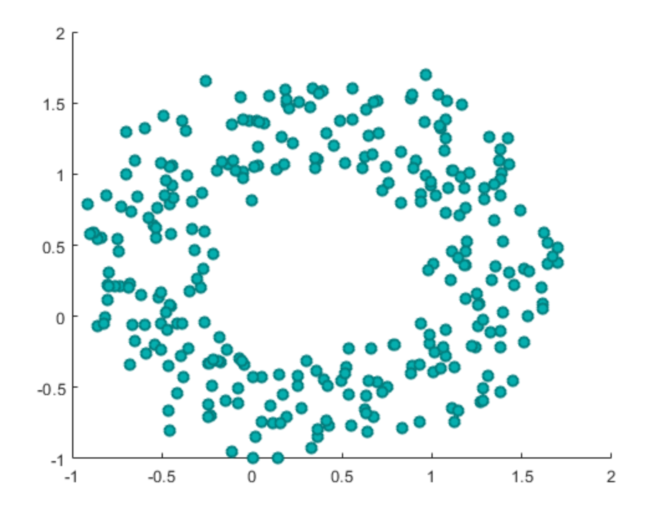
Where does each strategy fit best? How to combine them?

What do you see? How would you recreate this data distribution?



IRREGULAR VERBS

- A single verb can have various **word forms**:

(1) CREATE

a. create, creates, created, creating

b. creator, creation, creative, creatively

- (1a) is an example of **inflectional morphology**
  - expresses grammatical features
  - (usually) doesn't change basic meaning or part of speech

- **Grammatical features** are properties that the grammar of any language tracks and manifests
- Some features that English is sensitive to:
    - **number**: dog, dogs
    - **tense**: create, created
    - **gender**: he, she
    - **person**: we, yall, they
    - **mass/count**: 3 books, *3 bloods
    - **case**: I, me, my, mine

INFLECTIONAL PARADIGMS

- Word forms can track multiple features at once
- This can be tracked within an **inflectional paradigm**

CREATE

Present

	singular	plural
1	create	create
2	create	create
3	creates	create

Past

	singular	plural
1	created	created
2	created	created
3	created	created

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	singular	plural
1	created	created
2	created	created
3	created	created

- Only 3rd person singular is different – this looks easy!
  - Just add -s to the 3.sg present form and -d to all past forms!

Unfortunately, we all know there are **irregular verbs** in English

BE

Present

	singular	plural
1	am	are
2	are	are
3	is	are

Past

	singular	plural
1	was	were
2	were	were
3	was	were

IRREGULARS

Unfortunately, we all know there are **irregular verbs** in English

BE

Present

	singular	plural
1	am	are
2	are	are
3	is	are

Past

	singular	plural
1	was	were
2	were	were
3	was	were

- Darn, how do we get am or was from be?

Irregular verbs are arbitrary and follow no underlying pattern

BEST STRATEGY

Irregular verbs are arbitrary and follow no underlying pattern

- exhaustive listing
- rules and/or principles
- Machine Learning

FINITE PROBLEM SET

- Wikipedia lists about 200 English irregular verbs
  - including shrive, stave, gild
- This is a finite set
- Prediction is not important

PRONOUNS

Anaphora Expressions that depend on a contextual antecedent for their interpretation

Pronoun A type of anaphor that can replace a **Noun Phrase (NP)** (or Determiner Phrase)

Nominative

	singular	plural
1	I	we
2	you	you/yall/yinz
3	she/he/it	they

Accusative

	singular	plural
1	me	us
2	you	you/yall/yinz
3	her/him/it	them

In later years, holding forth to an interviewer or to an audience of aging fans at a comic book convention, Sam Clay liked to declare, apropos of *his* and Joe Kavalier's greatest creation, that back when *he* was a boy, sealed and hog-tied inside the airtight vessel known as Brooklyn, New York, *he* had been haunted by dreams of Harry Houdini. "To *me*, Clark Kent in a phone booth and Houdini in a packing crate, *they* were one and the same thing,"[...]

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- Connecting reference between expressions is non-trivial!

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- Using unambiguous reference sounds clunky and un-human
- Like the system has no idea what it's talking about


Next
Bitch, this is a beautiful
lake full of pure, clear water.
106

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PICKING A STRATEGY

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- ”Though this be madness, yet there is method in ’t.”

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- We actually probably have a pretty good idea of when we can use pronouns
- They seem to **corefer** with recently mentioned entities that match their description
- Let's try a rule:

(2) **Pronoun Rule 1**: If the entity is the same as the most recent entity with the same **features** (person, gender, number), a pronoun can be used

DOES IT WORK?

(3) a. Harry was in Gryffindor.
  b. **He** was friends with Ron.
  c. **He** had a pet rat.

- Who does He in (3c) refer to? Harry or Ron?

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- so why doesn't He corefer?
- It seems like linear order is too simplistic of an approach

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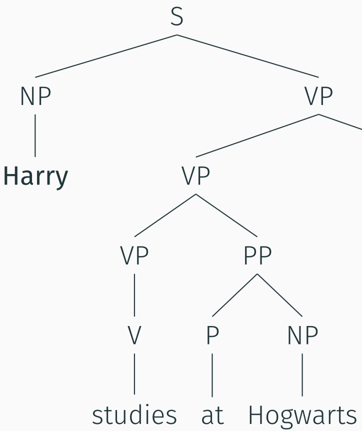
SALIENCY

- Pronouns (across sentences) are tracking **saliency**

  Salient: assumed to be in the **addressee**'s consciousness at the **utterance time**

(4) Harry studies at Hogwarts with Ron.

- Who is more salient? Harry? or Ron?
- Why?



- Subjects are structurally higher than objects
- In English this correlates with saliency

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- Pronoun distribution is based on known principles
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- Syntactic structure strongly influences saliency
- We can use Quill's understanding of a sentence's underlying structure to emulate this linguistic phenomenon

- Syntactic structure works as a strong indicator, but are there other factors at play?

OTHER FACTORS?

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- How would these interact with each other?

SENTENCE SELECTION

A typical Quill sentence:

(5) a. Aaron Young generated \$3M in revenue in 2016.

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(5) a. Aaron Young generated $3M in revenue in 2016.

b. Aaron Young's revenue was $3M in 2016.
c. Revenue for Aaron Young was $3M in 2016.
d. In 2016, Aaron Young generated $3M in revenue.
e. Aaron Young's 2016 generated revenue was $3M.

Sentence generation: only grammatical and accurate sentences should be **generated**

Sentence selection: the stylistically best sentence from the set of grammatical candidate sentences should be **selected**

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- but what determines a stylistically ‘good‘ sentence?

WHAT MAKES A GOOD SENTENCE?

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- is there even a right answer?

MULTIPLE AXES OF 'GOODNESS'

- There seem to be multiple factors involved:
    - length
    - subject choice
    - fronted information
    - strong verbs vs copulas (i.e. is/was)
    - …

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  - fronted information
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  - …
- These axes seem largely independent

EXTENSIBILITY

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- Humans are bad at keeping track of all possible permutations of interactions
  - Maybe we prefer active vs passive verbs, but what if that results in longer sentences?
- Different users also vary in how strongly they weight each factor

DID SOMEBODY SAY "WEIGHT"?

- Interaction of multiple features
- Features have varying importance
- Importances should be tuneable

DID SOMEBODY SAY "WEIGHT"?

- Interaction of multiple features
- Features have varying importance
- Importances should be tuneable
- This feels like a job for Machine Learning

Steps to utilizing Machine Learning for sentence selection:

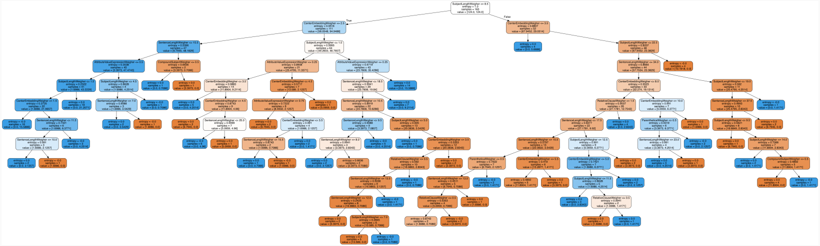
- Determine list of features that matter for style
- Build independent weighers for features
- Collect data
- Train the model on the data with respect to the features
- Use the model to select the best candidate sentence
- Lather, rinse, repeat

"TRAIN THE MODEL"

Not all models are the same:

- Regression
- Bayesian
- Neural Net
- Decision tree

LOST IN THE FOREST



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While the core decision is an ML problem, the inputs to that decision are still based on linguistic principles

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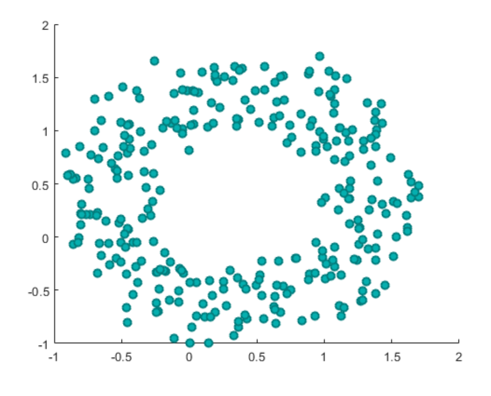
- Caveat: We need to be able to determine those features and how to track them
    - which often requires an understanding of the domain

CONCLUSION

What do you see?



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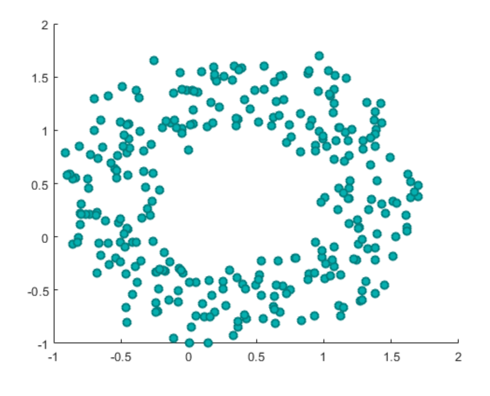

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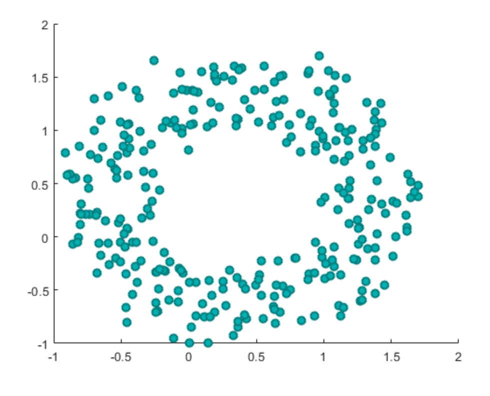

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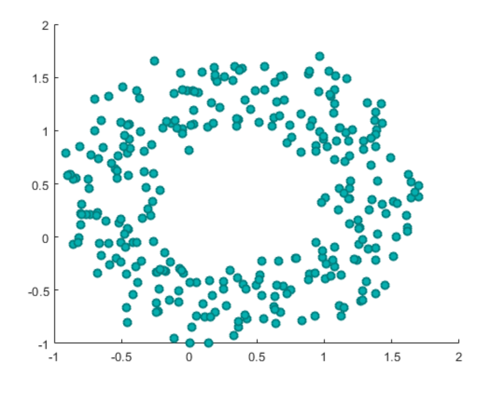

- **Irregular verbs:** discrete points
- **Pronouns**: conceptual circle → messy data
- **Sentence selection**: messy data → conceptual circle

Problems are often multi-faceted:

- Verb inflection does have regular rules
- Antecedent saliency for pronominal reference may have multiple factors
- Sentence selection features require principled analysis

CHIMERICAL SOLUTIONS

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  - from various perspectives: e.g. linguistics, comp sci, journalism,...
- and identifying stakeholders and external constraints
  - business requirements, deadlines, UX,...

Thank you!
Questions?

Get the source of this theme and the demo presentation from

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