narrative science

TACKLING NATURAL LANGUAGE GENERATION CHALLENGES AT NARRATIVE SCIENCE

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Oct 19, 2017

OVERVIEW

WHAT IS QUILL?

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.

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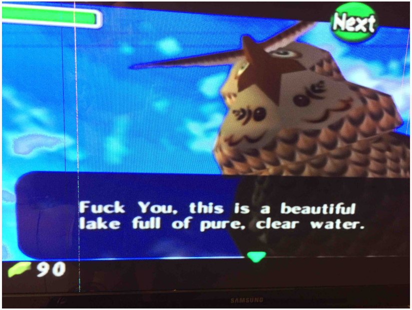

OTHER NLG

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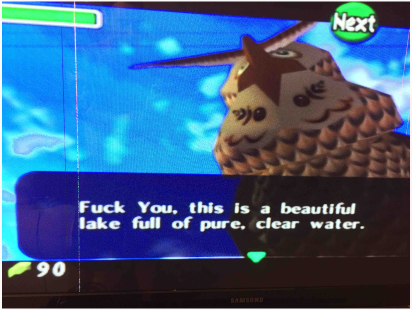

- What seems off here?

- Video games conversations have complex decision trees

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    - 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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    - Flexibility and linguistic creativity is limited and/or unscaleable in production
- 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

linguistically savvy & intent-driven

An advanced NLG system can dynamically generate language in response to a user's intents

- Templatic approaches
  - are only locally dynamic:
    e.g. easy to swap out a name or number, but harder to rearrange sentence structure
  - Language quality results from a complex decision tree with prebaked language at the leaves
- Neural nets
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- Neural nets
    - difficult to impossible to accurately convey a specific message
      e.g. a highly polished turd
    - user's intent has unreliable influence on language

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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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- 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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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

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

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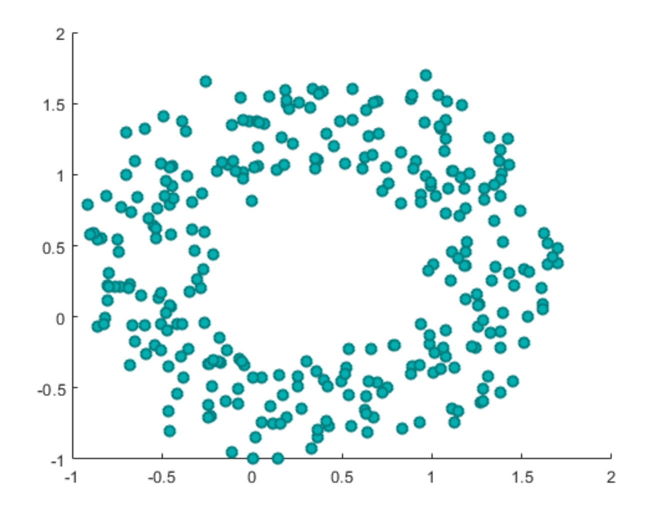
Where does each strategy fit best? How to combine them?

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



OUTLINE OF TALK

Overview

Irregular Verbs

Pronouns

Sentence Selection

Conclusion

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

- 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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Past

	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

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

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	singular	plural
1	am	are
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1	was	were
2	were	were
3	was	were

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

- There are rules for regular morphology
- Which verbs are irregular seems arbitrary
- How irregular verbs inflect also seems arbitrary
- Rules might be tough to derive
- Machine Learning may work, but do we actually want to overfit data?

- Wikipedia lists about 200 English irregular verbs, including shrive, stave, gild
- This is finite set, and most words aren't even that relevant
- Verb dictionaries exist
- There are subgroups within the irregulars
- It is feasible to exhaustively hardcode a list of all irregulars without rules or ML
- We can exactly fit the data without over- or undergeneralizing

PRONOUNS

Anaphora Expressions that depend on a contextual anteceent 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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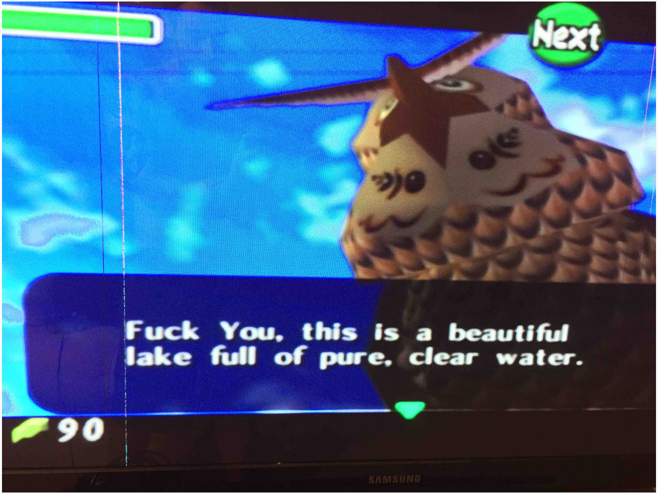
- Using unambiguous reference sounds clunky and un-human
- Like the system has no idea what it's talking about


Next
Fuck You, this is a beautiful
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90
SAMSUNG

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    - how arbitrary is the data?
- "Though this be madness, yet there is method in 't."

A PRINCIPLED APPROACH

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- We actually probably have a pretty good idea of when we can use pronouns

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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 of 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

(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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- It seems like linear order is too simplistic of an approach

SALIENCY

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

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(4) Harry studies at Hogwarts with Ron.

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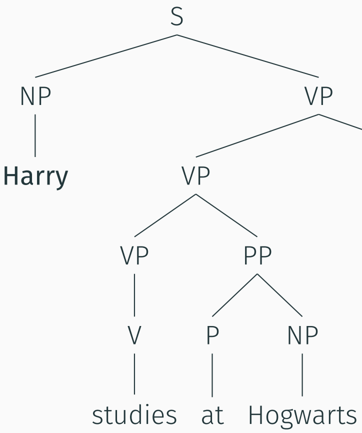

- Subjects are structurally higher than objects
- In English this correlates with saliency

TRACKING SALIENCY

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- We’ve seen that the syntactic structure strongly influences saliency
- Pronoun distribution appears to be based on known principles
- so lwe should ensure that the AI system also shares those principles

OTHER FACTORS?

- But are there other factors at play?

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    - recency
    - repitition
    - ??

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- But are there other factors at play?
  - recency
  - repitition
  - ??
- How would these interact with each other?

SENTENCE SELECTION

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

- but what determines a stylistically ‘good‘ sentence?

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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.

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- is there even a right answer?

MULTIPLE AXES OF 'GOODNESS'

- There seem to be multiple factors involved:
    - length
    - subject choice
    - values before attributes
    - fronted information
    - strong verbs vs copulas
    - …

MULTIPLE AXES OF 'GOODNESS'

- There seem to be multiple factors involved:
  - length
  - subject choice
  - values before attributes
  - fronted information
  - strong verbs vs copulas
  - ...
- These axes seem largely independent
- Different users also vary in how strongly they weight each factor

DID SOMEBODY SAY ”WEIGHT”?

- Sentence selection involves the interaction between several features
- The importance of these features is variable
- We would like to fine tune language style for each user

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- Sentence selection involves the interaction between several features
- The importance of these features is variable
- We would like to fine tune language style for each user
- This feels like a job for Machine Learning

LET THE MACHINE FIGURE OUT WHAT MATTERS

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

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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?
- Machines are much better at working with several (independent) features
- Humans are only responsible for building out each new feature

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- Trying to hand-tune sentence-selection for each user would be difficult
    - how to make a change in one place without breaking it elsewhere?
- Given an ML model, we can retrain the feature weights for each user

LESSONS AND CAVEATS

- Machine Learning is a good strategy for sentence selection
- Style is variable and involves the interaction between several features

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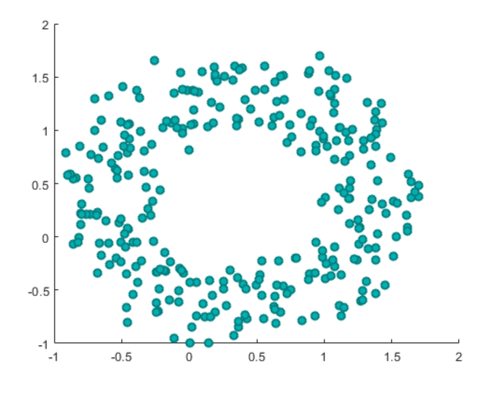
- Machine Learning is a good strategy for sentence selection
- Style is variable and involves the interaction between several features
- Caveat: We need to be able to determine those features and how to track them
    - which often requires an understanding of the domain

CONCLUSION

What do you see?



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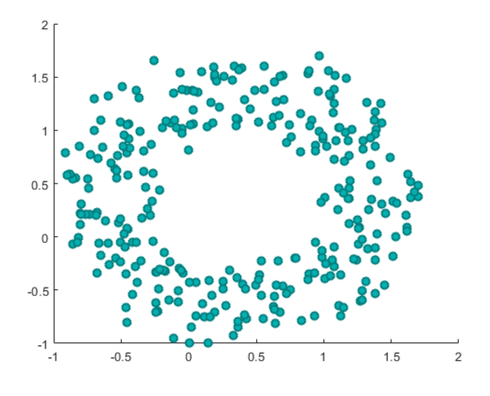

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PERSPECTIVES REDUX

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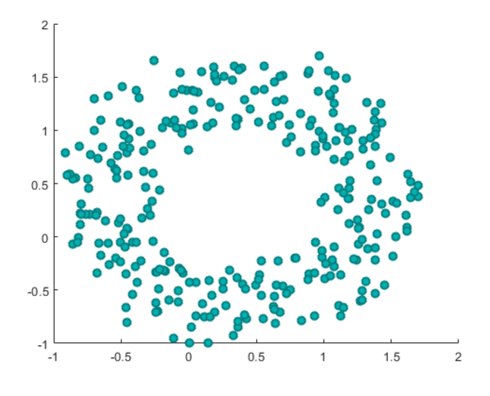

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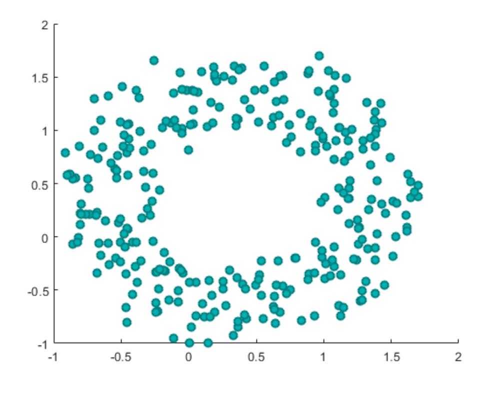

- **Irregular verbs:** discrete points
- **Pronouns**: conceptual circle → messy data
- **Sentence selection**: messy data → conceptual circle

CHIMERICAL PROBLEMS

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

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- Utilize whatever tools you have

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- but make sure those strategies are contingent on thoroughly assessing the nature of the problems
- which often requires having domain knowledge
    - go learn about what others have done in your field
    - from various perspectives: e.g. linguistics, comp sci, journalism,...

Thank you!
Questions?

Get the source of this theme and the demo presentation from

`github.com/matze/mtheme`