# TACKLING NATURAL LANGUAGE GENERATION CHALLENGES AT NARRATIVE SCIENCE

Mike Pham & Clayton Norris

Oct 19, 2017

Narrative Science

# 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.

# HOW IS THIS DIFFERENT THAN OTHER NLG?

So what?

# HOW IS THIS DIFFERENT THAN OTHER NLG?

So what?

- How is this different than Amazon sending me a templated email receipt of my recent purchases?

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?

# HOW IS THIS DIFFERENT THAN OTHER NLG?

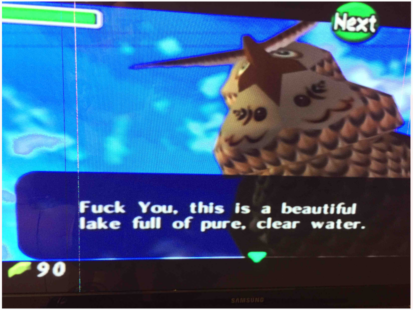
So what?

- 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

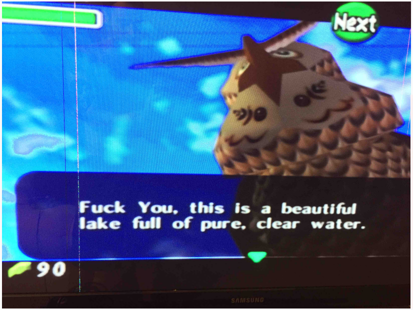
# OTHER NLG

## trigger warning: offensive language




# OTHER NLG

trigger warning: offensive language





- What seems off here?

## LIMITATIONS OF NLG

- 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

- 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
- Neural nets can learn from data to generate new language

- 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
- 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 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
    - difficult to impossible to accurately convey a specific message

## 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
    - difficult to impossible to accurately convey a specific message
      e.g. a highly polished turd
    - user's intent has unreliable influence on language

# GOALS FOR QUILL

- Accurately and dynamically convey the user's intents in natural language
- Language and ideas are **human-oriented**

- Accurately and dynamically convey the user's intents in natural language
- 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

# GOALS FOR QUILL

- Accurately and dynamically convey the user's intents in natural language
- 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

# NOT HUMAN-ORIENTED

What went wrong? Why isn't this useful to humans?

What went wrong? Why isn't this useful to humans?

- Ontology
  - The recipe doesn't understand what are reasonable ingredients and combinations
- Awareness

## NOT HUMAN-ORIENTED

What went wrong? Why isn't this useful to humans?

- Ontology
  - The recipe doesn't understand what are reasonable ingredients and combinations
  - Seafood probably shouldn't go into cookies
- Awareness

What went wrong? Why isn't this useful to humans?

- Ontology
  - The recipe doesn't understand what are reasonable ingredients and combinations
  - Seafood probably shouldn't go into cookies
  - You might also burn your house down trying to take its advice
- Awareness

# NOT HUMAN-ORIENTED

What went wrong? Why isn't this useful to humans?

- Ontology
  - The recipe doesn't understand what are reasonable ingredients and combinations
  - Seafood probably shouldn't go into cookies
  - You might also burn your house down trying to take its advice
- Awareness
  - Doesn't actually understand recipe structure

# NOT HUMAN-ORIENTED

What went wrong? Why isn't this useful to humans?

- Ontology
  - The recipe doesn't understand what are reasonable ingredients and combinations
  - Seafood probably shouldn't go into cookies
  - 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/

- What strategy to pick given these goals?

# HOW TO ACHIEVE THESE GOALS

- What strategy to pick given these goals?
- 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

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

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

- exhaustive listing

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

- exhaustive listing
- rules and/or principles

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

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

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

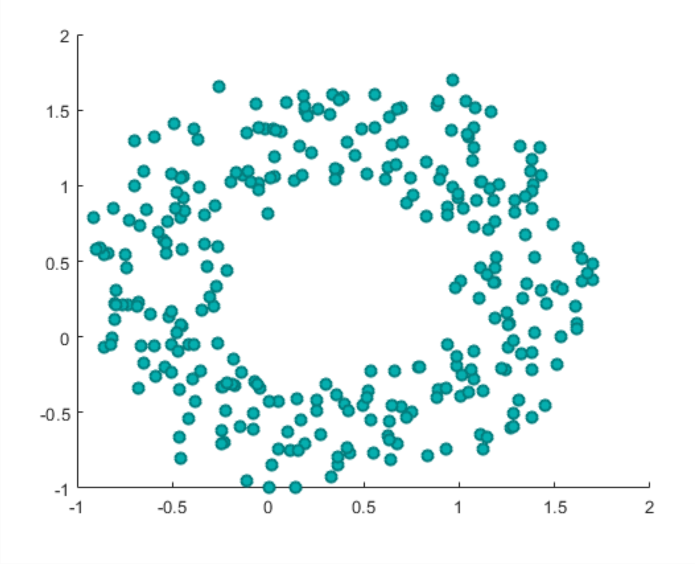
- exhaustive listing
- rules and/or principles
- Machine Learning

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

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

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

- **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 |

# 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 |

- 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?

# BEST STRATEGY

- 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?

# FINITE PROBLEM SET

- 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,"[...]

-Michael Chabon, The Amazing Adventures of Kavalier & Clay

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,"[...]

-Michael Chabon, The Amazing Adventures of Kavalier & Clay

- Connecting reference between expressions is non-trivial!

## PICKING A STRATEGY

- Strawman argument: hardcoding every possible instance to use a pronoun is out

- Strawman argument: hardcoding every possible instance to use a pronoun is out
- Machine Learning?

# PICKING A STRATEGY

- Strawman argument: hardcoding every possible instance to use a pronoun is out
- Machine Learning? Is likely possible...

# PICKING A STRATEGY

- Strawman argument: hardcoding every possible instance to use a pronoun is out
- Machine Learning? Is likely possible...
  - what are the features we want to track?
  - how arbitrary is the data?

# PICKING A STRATEGY

- Strawman argument: hardcoding every possible instance to use a pronoun is out
- Machine Learning? Is likely possible...
  - what are the features we want to track?
  - how arbitrary is the data?
- ”Though this be madness, yet there is method in ’t.”

- The distribution of pronouns is not arbitrary
- We actually probably have a pretty good idea of when we can use pronouns

- The distribution of pronouns is not arbitrary
- 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

- The distribution of pronouns is not arbitrary
- 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?

(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?
- Ron is the most salient singular masculine entity
- so why doesn't He corefer?

# 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?
- Ron is the most salient singular masculine entity
- so why doesn't He corefer?
- It seems like linear order is too simplistic of an approach

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

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

# 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.

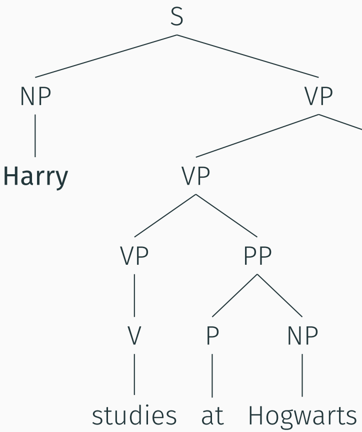
- Who is more salient? Harry? or Ron?

- 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

- An advanced NLG system should track saliency in order to use pronouns
- We've seen that the syntactic structure strongly influences saliency

# TRACKING SALIENCY

- An advanced NLG system should track saliency in order to use pronouns
- 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?

- But are there other factors at play?
    - recency
    - repitition
    - ??

- 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**

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**

- but what determines a stylistically ‘good‘ sentence?

## WHAT MAKES A GOOD SENTENCE?

- Most native speakers will agree when a sentence is grammatical
- But style is vague and elusive, varying from person to person

# WHAT MAKES A GOOD SENTENCE?

- Most native speakers will agree when a sentence is grammatical
- But style is vague and elusive, varying from person to person
- Which do think is the best sentence?

(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.

# WHAT MAKES A GOOD SENTENCE?

- Most native speakers will agree when a sentence is grammatical
- But style is vague and elusive, varying from person to person
- Which do think is the best sentence?

(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.

- 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
  - …

- 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

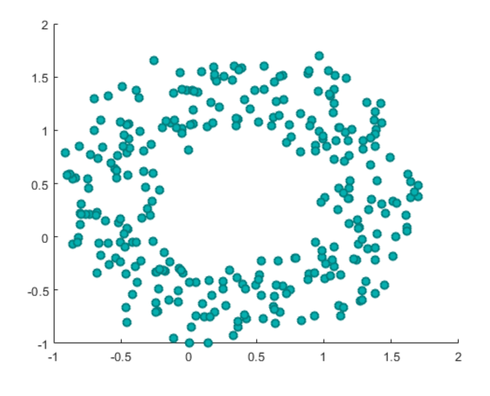
# DID SOMEBODY SAY "WEIGHT"?

- 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
- This feels like a job for Machine Learning

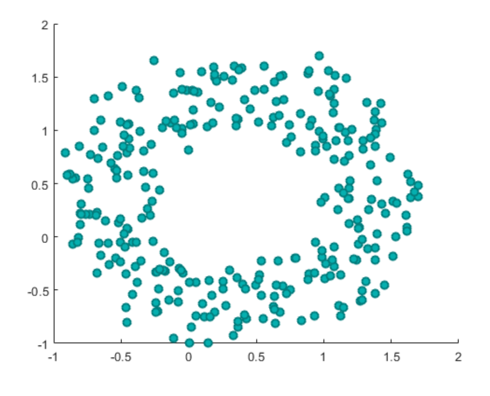
blah blah more sentence selection stuff

# CONCLUSION

What do you see?

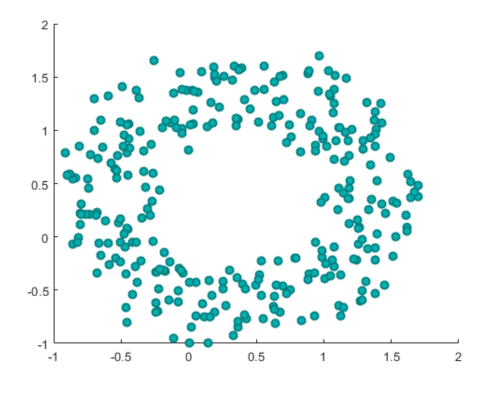


What do you see?



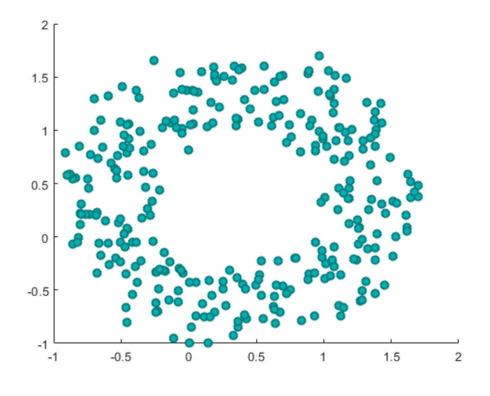

- **Irregular verbs:** discrete points

What do you see?




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

What do you see?




- **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

Things we've learned creating advanced NLG:

- Strategies for tackling problems should not (always) be monolithic
- Utilize whatever tools you have

Things we've learned creating advanced NLG:

- Strategies for tackling problems should not (always) be monolithic
- Utilize whatever tools you have
- but make sure those strategies are contingent on thoroughly assessing the nature of the problems

## CHIMERICAL SOLUTIONS

Things we’ve learned creating advanced NLG:

- Strategies for tackling problems should not (always) be monolithic
- Utilize whatever tools you have
- but make sure those strategies are contingent on thoroughly assessing the nature of the problems
- which often requires having domain knowledge

Things we’ve learned creating advanced NLG:

- Strategies for tackling problems should not (always) be monolithic
- Utilize whatever tools you have
- 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

Things we've learned creating advanced NLG:

- Strategies for tackling problems should not (always) be monolithic
- Utilize whatever tools you have
- 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`