ANLP Lecture 29: Gender Bias in NLP

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Recap

- Some co-reference examples can't be solved by agreement, syntax, or other local features, but require semantic information ("world knowledge"?):

The [city council]$_i$ denied [the demonstrators]$_j$ a permit because…
…[they]$_i$ feared violence.
…[they]$_j$ advocated violence.

- NLP systems don't observe the world directly, but do learn from what people talk/write about.
- With enough text, this seems to work surprisingly well…
  - … but may also reproduce human biases, or even amplify or introduce new ones (depending on what we talk about and how).

Example: gender bias

The secretary read the letter to the workers. He was angry.

The secretary read the letter to the workers. She was angry.

- People have a harder time processing **anti-stereotypical** examples than **pro-stereotypical** examples.
- What about NLP systems? Is there algorithmic bias? E.g., do NLP systems
  - Produce more errors for female entities than males?
  - Perpetuate or amplify stereotypical ideas or representations?

Today's lecture

- What are some examples of gender bias in NLP and what consequences might these have?
- What is a challenge dataset and how are these used to target specific problems like gender bias?
- For one specific example (gender bias in coreference),
  - How can we systematically measure (aspects of) this bias?
  - What are some sources of the bias?
  - What can be done to develop systems that are less biased?

Biased scores in coref, language modelling

- Internal scores indicate implicit bias in coreference resolution and language modelling (Lu et al., 2019):

$1_\square$: The **doctor** ran because **he** is late. (5.08)	$1_\square$: **He** is a | **doctor**.	-9.72
$1_\bigcirc$: The **doctor** ran because **she** is late. (1.99)	$1_\bigcirc$: **She** is a | **doctor**.	-9.77
$2_\square$: The **nurse** ran because **he** is late. (−0.44)	$2_\square$: **He** is a | **nurse**.	-8.99
$2_\bigcirc$: The **nurse** ran because **she** is late. (5.34)	$2_\bigcirc$: **She** is a | **nurse**.	-8.97
(a) Coreference resolution	(b) Language modeling	$\ln \Pr[B \mid A]$

Figure 1: Examples of gender bias in coreference resolution and language modeling as measured by coreference scores (left) and conditional log-likelihood (right).

Machine translation errors

- Translating from English to Hungarian or Turkish (no gender) and back to English:

She is a janitor. He is a nurse.

↓

He's a janitor. She is a nurse.

- Translating English to Spanish (all nouns have gender).
  - Female doctor becomes male; nurse becomes female:

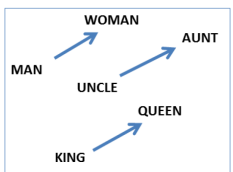
The doctor asked the nurse to help **her** in the procedure

El doctor le pidio a la enfermera que le ayudara con el procedimiento

Example 1: Google Translate, 17 Nov 2019; Example 2 from Stanovsky et al. (2019)

Word embeddings

- Famously, word embeddings can (approximately) solve analogies like `man:king :: woman:x`
  - Nearest vector to $v_{man} - v_{woman} + v_{king}$ is v_{queen}



- Almost as famously, pretrained word2vec vectors also say `man:computer programmer :: woman:homemaker` (Bolukbasi, 2016).
  - All due to word associations in the training data!

Figure: Mikolov et al. (2013)

Two kinds of implications

- Representation bias: when systems negatively impact the representation (social identity) of certain groups.
  - Implying that women should be homemakers
  - Guessing that doctors are male when translating from Hungarian.
  - Rating sentences with female noun phrases as more likely to be angry.
- Allocation bias: unfairly allocating resources to some groups.
  - Recommending to interview qualified men more often than qualified women because of irrelevant male-oriented words in their CVs that are similar to those in existing employees' CVs.

See Sun et al. (2017), citing Crawford (2017) and others.

Gender bias in coreference resolution

- Zhao et al. (2018) present work where they
  - Create a **challenge dataset** to quantify gender bias in co-reference systems.
  - Show significant gender bias in three different types of systems.
  - Identify some sources of bias and ways to de-bias systems.

Challenge dataset

- Most NLP systems are trained and tested on text sampled from natural sources (news, blogs, Twitter, etc)
- These can tell us how well systems do on average, but harder to understand specific strengths/weaknesses
- One way to investigate these: design a dataset specifically to test them.
- Typically small and used only for (dev and) test; training is still on original datasets.

The WinoBias dataset

- Based on Winograd schema idea; tests gender bias using pairs of pro-/anti-stereotypical sentences:

Pro: [The physician]$_i$ hired [the secretary]$_j$ because [he]$_i$ was overwhelmed with clients.
Anti: [The physician]$_i$ hired [the secretary]$_j$ because [she]$_i$ was overwhelmed with clients.

Pro: [The physician]$_i$ hired [the secretary]$_j$ because [she]$_j$ was highly recommended.
Anti: [The physician]$_i$ hired [the secretary]$_j$ because [he]$_j$ was highly recommended.

- Compute the difference in average accuracy between pro-stereotypical and anti-stereotypical sentences.

The WinoBias dataset

- Also includes "Type 2" sentence pairs, such as:

Pro: [The physician]$_i$ called [the secretary]$_j$ and told [her]$_j$ to cancel the appointment.
Anti: [The physician]$_i$ called [the secretary]$_j$ and told [him]$_j$ to cancel the appointment.

- What's different about these? Would you expect them to show more or less bias than Type 1 pairs (below)? Why?

Pro: [The physician]$_i$ hired [the secretary]$_j$ because [he]$_i$ was overwhelmed with clients.
Anti: [The physician]$_i$ hired [the secretary]$_j$ because [she]$_i$ was overwhelmed with clients.

Pro: [The physician]$_i$ hired [the secretary]$_j$ because [she]$_j$ was highly recommended.
Anti: [The physician]$_i$ hired [the secretary]$_j$ because [he]$_j$ was highly recommended.

The WinoBias dataset

- In Type 2, the pronoun can syntactically **only** refer to one of the entities (otherwise would need reflexive).

Pro: [The physician]$_i$ called [the secretary]$_j$ and told [her]$_j$ to cancel the appointment.

Anti: [The physician]$_i$ called [the secretary]$_j$ and told [him]$_j$ to cancel the appointment.

- In Type 1, both possibilities are syntactically allowed; only the semantics constrains the resolution.

Pro: [The physician]$_i$ hired [the secretary]$_j$ because [he]$_i$ was overwhelmed with clients.

Anti: [The physician]$_i$ hired [the secretary]$_j$ because [she]$_i$ was overwhelmed with clients.

- So, if systems learn/use syntactic info as well as semantics, then Type 2 should be easier and less susceptible to bias.

Constructing the pairs

- Used US Labor statistics to choose 40 occupations ranging from male-dominated to female-dominated.
  - (might not be so in other countries!)
- Constructed 3160 sentences according to templates:
  - **Type 1:** [entity1] [interacts with] [entity2] [conjunction] [pronoun] [circumstances]
  - **Type 2:** [entity1] [interacts with] [entity2] and then [interacts with] [pronoun] [circumstances]

Testing coreference systems

- Three systems are tested on WinoBias:
  - Rule-based (Stanford Deterministic Coreference System, 2010)
  - Feature-based Log-linear (Berkeley Coreference Resolution System, 2013)
  - Neural (UW End-to-end Neural Coreference Resolution System, 2017)
- Rule-based doesn't train; others are trained on OntoNotes 5.0 corpus.

Out-of-the-box results

- Yes, systems are biased… (numbers are F1 scores)

Method	T1-pro	T1-anti	T1-Diff	T2-pro	T2-anti	T2-Diff
Neural	76.0	49.4	26.6	88.7	82.0	13.5
Feature	66.7	56.0	10.6	73.0	65.2	15.7
Rule	76.7	37.5	39.2	50.5	39.9	21.3

- All systems do much better on Pro than Anti (large Diff).
- For Neural and Rule, Diff is much bigger for Type 1 (T1) than Type 2 (T2), as expected.
- For Feature, Diff is larger for T2: unexpected, and paper does not comment on possible reasons!

Likely reasons

- Biases in immediate training data: Like many corpora, OntoNotes itself is biased.
  - 80% of mentions headed by gendered pronoun are male.
  - Male gendered mentions are >2x as likely to contain a job title as female mentions.
  - OntoNotes contains various genres; same trends hold for all of them.
- Biases in other resources used:
  - For example, the pre-trained word embeddings used by some of the systems.

Augmenting data by gender-swapping

To address the bias in OntoNotes, Zhao et al. create additional training data by gender-swapping the original data, as follows.

1. Anonymize named entities

French President **Emmanuel Macron** appeared today ... Mr. **Macron** has been criticized for his ... He announced his ...

French President **E1 E2** appeared today ... Mr. **E2** has been criticized for his ... He announced his ...

Augmenting data by gender-swapping

2. Create a dictionary of gendered terms and their gender-swapped versions, e.g.

she ↔ he, her ↔ him, Mrs. ↔ Mr., mother ↔ father

3. Replace gendered terms with their gender-swapped versions:

French President E1 E2 appeared today ... **Mr.** E2 has been criticized for **his** ... He announced **his** ...

French President E1 E2 appeared today ... **Mrs.** E2 has been criticized for **his** ... **She** announced **her** ...

Additional methods

- Reduce gender bias in pre-trained word embeddings using methods from Bolukbasi et al. (2016)
- Gender balance frequencies in other word lists obtained from external resources.

Final results

- After applying all de-biasing methods:

Method	T1-pro	T1-anti	T1-Diff	T2-pro	T2-anti	T2-Diff
Neural	63.9	62.8	1.1	81.3	83.4	-2.1
Feature	62.3	60.4	1.9	71.1	68.6	2.5

- The Diffs are all much smaller (in fact, mostly no longer statistically significant).

Interim discussion

- Is what I've said so far enough to conclude that
  - Co-ref systems are likely to produce incorrect results in anti-stereotypical sentences?
  - The proposed de-biasing methods remove gender bias from co-ref systems?
  - We should use these methods for new systems?
- If not, what further evidence would help answer these questions? What other questions should we be asking?

Results on OntoNotes

- Are co-ref systems likely to produce incorrect results in anti-stereotypical sentences?
  - On challenge data set, yes!
  - What about on more typical text?
- To see, evaluate on anonymized OntoNotes dev set, original vs gender-swapped:

Model	Original	Swapped
Neural	66.4	65.9
Feature	61.3	60.3

  - Suggests that on easy (in-domain) cases, gender bias isn't likely to cause many errors (good news!)
  - But real out-of-domain cases are probably somewhere between OntoNotes and WinoBias, and WinoBias shows that hard cases do cause errors!

Did we remove all bias from the systems?

- Maybe. But we can't conclude gender bias is gone (or negligible) even if Diff is close to zero.
  - WinoBias only tests a particular type of sentence.
  - Gender bias might affect other types of sentences that weren't measured.
- An example of a one-way test (similar to statistical hypothesis tests and many other scientific experiments):
  - Can provide evidence that bias does exist
  - Lack of evidence does not mean no bias exists

Should we always use these methods?

- We probably want to know whether doing so negatively impacts results on more typical cases, and if so how much.
- In this case, only slightly.
  Results on OntoNotes dev:

Model	Out-of-box	De-biased
Neural	67.7	66.3
Feature	61.7	61.0

- A bigger impact would cause a bigger ethical dilemma, and motivate developing a better method.
- We also don't know whether/how well this method applies to other datasets/languages/etc.

Where does it leave us?

- So, still leaves open questions, but a good start towards measuring and reducing gender bias in coreference systems.
- Algorithmic bias (gender and otherwise) is a growing area of research in NLP.
- For other tasks, see recent review of work on mitigating gender bias in NLP by Sun et al. (2019).

Questions for review

- What are some examples of gender bias in NLP and what consequences might these have?
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- For one specific example (gender bias in coreference),
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