Accessible Abstract: The data used to train computer question answering systems have three times as many men as women. This paper examines whether this is a problem for question answering accuracy. After a thorough investigation, we do not find evidence of serious accuracy discrepancies between languages. However, an absence of evidence is not evidence of absence, and we would argue that we need more diverse datasets to better represent the world’s population.

Links:
- Research Talk [https://youtu.be/Hopd3oHfoYk](https://youtu.be/Hopd3oHfoYk)

Downloaded from [http://umiacs.umd.edu/~jbg/docs/2021_emnlp_qa_fairness.pdf](http://umiacs.umd.edu/~jbg/docs/2021_emnlp_qa_fairness.pdf)

Contact Jordan Boyd-Graber (jbg@boydgraber.org) for questions about this paper.
Toward Deconfounding the Influence of Entity Demographics for Question Answering Accuracy

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Abstract

The goal of question answering (QA) is to answer any question. However, major QA datasets have skewed distributions over gender, profession, and nationality. Despite that skew, model accuracy analysis reveals little evidence that accuracy is lower for people based on gender or nationality; instead, there is more variation on professions (question topic). But QA’s lack of representation could itself hide evidence of bias, necessitating QA datasets that better represent global diversity.

1 Introduction

Question answering (QA) systems have impressive recent victories—beating trivia masters (Ferrucci et al., 2010) and superhuman reading (Najberg, 2018)—but these triumphs hold only if they generalize: QA systems should be able to answer questions even if they do not look like training examples. While other work (Section 4) focuses on demographic representation in NLP resources, our focus is how well QA models generalize across demographic subsets.

After mapping mentions to a knowledge base (Section 2), we show existing QA datasets lack diversity in the gender and national origin of the people mentioned: English-language QA datasets mostly ask about US men from a few professions (Section 2.2). This is problematic because most English speakers (and users of English QA systems) are not from the US or UK. Moreover, multilingual QA datasets are often translated from English datasets (Lewis et al., 2020; Artetxe et al., 2019). However, no work has verified that QA systems generalize to infrequent demographic groups.

Section 3 investigates whether statistical tests reveal patterns on demographic subgroups. Despite skewed distributions, accuracy is not correlated with gender or nationality, though it is with professional field. For instance, Natural Questions (Kwiatkowski et al., 2019, NQ) systems do well with entertainers but poorly with scientists, which are handled well in TriviaQA. However, absence of evidence is not evidence of absence (Section 5), and existing QA datasets are not yet diverse enough to vet QA’s generalization.

2 Mapping Questions to Entities

We analyze four QA tasks: NQ,1 SQuAD (Rajpurkar et al., 2016), QB (Boyd-Graber et al., 2012) and TriviaQA (Joshi et al., 2017). Google CLOUD-NL2 finds and links entity mentions in QA examples.3

<table>
<thead>
<tr>
<th>Entity Type</th>
<th>NQ Train</th>
<th>Dev</th>
<th>QB Train</th>
<th>Dev</th>
<th>SQuAD Train</th>
<th>Dev</th>
<th>TriviaQA Train</th>
<th>Dev</th>
</tr>
</thead>
<tbody>
<tr>
<td>Person</td>
<td>32.14</td>
<td>32.27</td>
<td>58.49</td>
<td>57.18</td>
<td>14.56</td>
<td>9.56</td>
<td>40.89</td>
<td>40.69</td>
</tr>
<tr>
<td>No entity</td>
<td>21.97</td>
<td>22.61</td>
<td>15.88</td>
<td>20.13</td>
<td>37.27</td>
<td>47.95</td>
<td>14.85</td>
<td>14.93</td>
</tr>
<tr>
<td>Location</td>
<td>28.42</td>
<td>27.82</td>
<td>34.50</td>
<td>35.11</td>
<td>33.52</td>
<td>29.34</td>
<td>44.32</td>
<td>44.00</td>
</tr>
<tr>
<td>Work of art</td>
<td>17.31</td>
<td>16.19</td>
<td>27.98</td>
<td>28.16</td>
<td>3.15</td>
<td>1.15</td>
<td>17.53</td>
<td>17.76</td>
</tr>
<tr>
<td>Other</td>
<td>2.66</td>
<td>2.70</td>
<td>9.83</td>
<td>9.88</td>
<td>5.08</td>
<td>3.10</td>
<td>14.38</td>
<td>14.61</td>
</tr>
<tr>
<td>Organization</td>
<td>17.73</td>
<td>18.05</td>
<td>20.37</td>
<td>17.78</td>
<td>21.34</td>
<td>19.14</td>
<td>22.15</td>
<td>21.14</td>
</tr>
<tr>
<td>Event</td>
<td>8.15</td>
<td>8.89</td>
<td>8.75</td>
<td>8.75</td>
<td>3.16</td>
<td>3.01</td>
<td>8.59</td>
<td>8.73</td>
</tr>
<tr>
<td>Product</td>
<td>0.85</td>
<td>1.06</td>
<td>0.84</td>
<td>0.63</td>
<td>1.39</td>
<td>0.33</td>
<td>3.99</td>
<td>3.99</td>
</tr>
<tr>
<td>Total Examples</td>
<td>106926</td>
<td>2011130327</td>
<td>221613019</td>
<td>1197137622</td>
<td>11313</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 1: Coverage (% of examples) of entity-types in QA datasets. Since examples can mention more than one entity, columns can sum to >100. Most datasets except SQuAD are rich in people.

2.1 Focus on People

Many entities appear in examples (Table 1) but people form a majority in our QA tasks (except SQuAD). Existing work in AI fairness focuses on disparate impacts on people, and models harm especially when it comes to people; hence, our primary intent is to understand how demographic characteristics of “people” correlate with model correctness.

The people asked about in a question can be in the answer—“who founded Sikhism?” (A: Guru

∗ Work completed while at Google Research

1For NQ, we only consider questions with short answers.
2https://cloud.google.com/natural-language/docs/
analyzing-entities
3We analyze the dev fold, which is consistent with the training fold (Table 1 and 2), as we examine accuracy.
Demographics are a natural way to categorize these entities and we consider the high-coverage demographic characteristics from Wikidata. Given an entity, Wikidata has good coverage for all datasets: gender (> 99%), nationality (> 93%), and profession (> 94%). For each characteristic, we use the knowledge base to extract the specific value for a person (e.g., the value “poet” for the characteristic “profession”). However, the values defined by Wikidata have inconsistent granularity, so we collapse near-equivalent values (e.g., “writer”, “author”, “poet”, etc. See Appendix A.1–A.2 for an exhaustive list). For questions with multiple values (where multiple entities appear in the answer, or a single entity has multiple values), we create a new value concatenating them together. An ‘others’ value subsumes values with fewer than fifteen examples; people without a value become ‘not found’ for that characteristic.

Three authors manually verify entity assignments by vetting fifty random questions from each dataset. Questions with at least one entity had near-perfect 96% inter-annotator agreement for CLOUD-NL’s annotations, while for questions where CLOUD-NL didn’t find any entity, agreement is 98%. Some errors were benign: incorrect entities sometimes retain correct demographic values; e.g., Elizabeth II instead of Elizabeth I. Other times, coarse-grained nationality ignores nuance, such as the distinction between Greece and Ancient Greece.

2.2 Who is in Questions?

Our demographic analysis reveals skews in all datasets, reflecting differences in task focus (Table 2). NQ are search queries and skew toward popular culture. QB nominally reflects an undergraduate curriculum and captures more “academic” knowledge. TriviaQA is popular trivia, and SQuAD reflects Wikipedia articles.

Across all datasets, men are asked about more than women, and the US is the subject of the majority of questions except in TriviaQA, where the plurality of questions are about the UK. NQ has the highest coverage of women through its focus on entertainment (Film/TV, Music and Sports).

3 What Questions can QA Answer?

QA datasets have different representations of demographic characteristics; is this focus benign or do these differences carry through to model accuracy?

We analyze a SOTA system for each of our four tasks. For NQ and SQuAD, we use a fine-tuned BERT (Alberti et al., 2019) with curated training data (e.g., downsampling questions without answers and split documents into multiple training instances). For the open-domain TriviaQA task, we use ORQA (Lee et al., 2019) with a BERT-based reader and retriever components. Finally, for QB, we use the competition winner from Wallace et al. (2019), a BERT-based reranker of a TF-IDF retriever. Accuracy (exact-match) and average F1 are both common QA metrics (Rajpurkar et al., 2016). Since both are related and some statistical tests require binary scores, we focus on exact-match.

Rather than focus on aggregate accuracy, we focus on demographic subsets’ accuracy (Figure 1). For instance, while 66.2% of questions about people are correct in QB, the number is lower for the Dutch (Netherlands) (55.6%) and higher for Ireland (87.5%). Unsurprisingly, accuracy is consistently low on the ‘not_found’ subset, where Wikidata lacks a person’s demographic value.

Are the differences we observe across strata significant? We probe this in two ways: using $\chi^2$ tests (Plackett, 1983) to see if trends exist and using logistic regression to explore those that do.
3.1 Do Demographic Values Affect Accuracy?

The $\chi^2$ test is a non-parametric test of whether two variables are independent. To see if accuracy and characteristics are independent, we apply a $\chi^2$ test to a $n \times 2$ contingency table with $n$ rows representing the frequency of that characteristic’s subsets contingent on whether the model prediction is correct or not (Table 3). If we reject the null with a Bonferroni correction (Holm, 1979, divide the $p$-value threshold by three, as we have multiple tests for each dataset), that suggests possible relationships: gender in NQ ($p = 2.36 \times 10^{-12}$) and professional field in NQ ($p = 0.0142$), QB ($p = 2.34 \times 10^{-7}$) and TriviaQA ($p = 0.0092$). However, we find no significant relationship between nationality and accuracy in any dataset.

While $\chi^2$ identifies which characteristics impact model accuracy, it does not characterize how. For instance, $\chi^2$ indicates NQ’s gender is significant, but is this because accuracy is higher for women, or because the presence of both genders in examples lowers the accuracy?

3.2 Exploration with Logistic Regression

Thus, we formulate a simple logistic regression: can an example’s demographic values predict if a model answers correctly? Logistic regression and related models are the workhorse for discovering and explaining the relationship between variables in history (McCloskey and McCloskey, 1987), education (van der Linden and Hambleton, 2013), political science (Poole and Rosenthal, 2011), and sports (Glickman and Jones, 1999). Logistic regression is also a common tool in NLP: to find linguistic constructs that allow determiner omission (Kiss et al., 2010) or to understand how a scientific paper’s attributes effect citations (Yogatama et al., 2011). Unlike model calibration (Niculescu-Mizil and Caruana, 2005), whose goal it to maximize prediction accuracy, the goal here is explanation.

We define binary features for demographic values which characteristics impact model accuracy, it does not characterize how. For instance, $\chi^2$ indicates NQ’s gender is significant, but is this because accuracy is higher for women, or because the presence of both genders in examples lowers the accuracy?

Exhaustive list of demographic features in the Appendix.
person-entities and multiple gold-answers (scaled with the base two logarithm).

But that is not the only reason an answer may be difficult or easy. Following Sugawara et al. (2018), we incorporate features that reveal the questions’ difficulty. For instance, questions that clearly hint the answer type reduce ambiguity. The \( t_{\text{who}} \) checks if the token “who” is in the start of the question. Similarly, \( t_{\text{what}}, t_{\text{when}}, \) and \( t_{\text{where}} \) capture other entity-types. Questions are also easier if evidence only differs from the question by a couple of words; thus, \( q_{\text{sim}} \) is the Jaccard similarity between question and evidence tokens. Finally, the binary feature \( e_{\text{train\_count}} \) marks if the person-entities occur in the training data more than twice.

We first drop features with negligible effect on accuracy using LASSO (regularization \( \lambda = 1 \)) by removing zero coefficients. For the remaining features, Wald statistics (Fahrmeir et al., 2007) estimate \( p \)-values. Although we initially use quadratic features they are all eliminated during feature reduction. Thus, we only report the linear features with a minimal significance (\( p \)-value < 0.1).

3.3 How do Properties Affect Accuracy?

Recall that logistic regression uses features to predict whether the QA system will get the answer right or not. Features associated with correct answers have positive weights (like those derived from Sugawara et al. (2018), \( q_{\text{sim}} \) and \( e_{\text{train\_count}} \)), those associated with incorrect answers have negative weights, and features without effect will be near zero. Among the \( t_{\text{who}} \) features, \( t_{\text{who}} \) significantly correlates with model correctness, especially in NQ and QB, where questions asked directly about a person.

However, our goal is to see if, after accounting for obvious reasons a question could be easy, demographic properties can explain QA accuracy. The strongest effect is for professions (Table 4). For instance, while NQ and QB systems struggle on science questions, TriviaQA’s does not. Science has roughly equivalent representation (Table 2), suggesting QB questions are harder.

While \texttt{multi\_answer} (and \texttt{multi\_entities}) reveal harder NQ questions, it has a positive effect in TriviaQA, as TriviaQA uses multiple answers for alternate formulations of answers (Appendix B.2.1, B.2.2), which aids machine reading, while multiple NQ answers are often a sign of ambiguity (Boyd-Graber and Börschinger, 2020; Si et al., 2021):

\[ \text{“Who says that which we call a rose?” A: Juliet, A: William Shakespeare.} \]

For male and female genders, NQ has no statistically significant effect on accuracy, only questions about entities with multiple genders depresses accuracy. Given the many findings of gender bias in NLU (Zhao et al., 2017; Webster et al., 2018; Zhao et al., 2018; Stanovsky et al., 2019), this is surprising. However, we caution against accepting this conclusion without further investigation given the strong correlation of gender with professional field (Goulden et al., 2011), where we do see significant effects.

Taken together, the \( \chi^2 \) and logistic regression analysis give us reason to be optimistic: although data are skewed for all subsets, QA systems might well generalize from limited training data across gender and nationality.

4 Related Work

Language is a reflection of culture. Like other cultural artifacts—encyclopedias (Reagle and Rhue, 2011), and films (Sap et al., 2017)—QA has more men than women. Other artifacts like children’s books have more gender balance but reflect other aspects of culture (Larrick, 1965).

The NLP literature is also grappling with demographic discrepancies. Standard coreference systems falter on gender-balanced corpora (Webster et al., 2018), and Zhao et al. (2018) create synthetic training data to reduce bias. Similar coreference issues plague machine translation systems (Stanovsky et al., 2019), and Li et al. (2020) use QA to probe biases of NLP systems. Sen and Saffari (2020) show that there are shortcomings in QA datasets and evaluations by analysing their out-of-domain generalization capabilities and ability to handle question variation. Joint models of vision and language suggest that biases come from language, rather than from vision (Ross et al., 2021). However, despite a range of mitigation techniques (Zhao et al., 2017; inter alia) none, to our knowledge, have been successfully applied to QA, especially from the demographic viewpoint.

5 Discussion and Conclusion

This paper delivers both good news and bad news. While datasets remain imperfect and reflect societal imperfections, for many demographic properties, we do not find strong evidence that QA suffers from this skew.

However, this is an absence of evidence rather
| Dataset      | Features           | Coef | SE   | Wald (|W|) | Z   | P  | $\mathbb{P}_{Z \sim N(|Z| > |W|)}$ |
|--------------|--------------------|------|------|--------|-----|----|-----------------------------------|
| NQ           | bias               | 1.964| 0.727| 2.703  | 0.0069 | *** |
|              | multi_answers      | -1.893| 0.438| 4.327  | 0.0000 | **** |
|              | o_not_found        | -1.112| 0.514| 2.163  | 0.0305 | **  |
|              | t_who              | +0.773| 0.280| 2.764  | 0.0057 | *** |
|              | o_science/tech     | -0.715| 0.390| 1.832  | 0.0670 | *   |
|              | multi_entities     | -0.678| 0.342| 1.979  | 0.0478 | **  |
|              | q_sim              | +0.406| 0.210| 1.934  | 0.0531 | *   |
|              | e_train_count      | +0.353| 0.178| 1.979  | 0.0479 | **  |
|QB            | e_train_count      | +1.922| 0.269| 7.144  | 0.0000 | **** |
|              | bias               | -1.024| 0.291| 3.516  | 0.0004 | **** |
|              | o_film/tv          | -0.910| 0.470| 1.934  | 0.0531 | *   |
|              | multi_entities     | -0.870| 0.165| 5.287  | 0.0000 | **** |
|              | o_science/tech     | -0.667| 0.265| 2.522  | 0.0117 | **  |
|              | o_religion         | -0.655| 0.362| 1.812  | 0.0700 | *   |
|              | o_writing          | +0.402| 0.189| 2.128  | 0.0334 | **  |
|              | t_who              | +0.363| 0.183| 1.990  | 0.0466 | **  |
|TriviaQA      | bias               | -1.066| 0.114| 9.353  | 0.0000 | **** |
|              | o_religion         | -0.443| 0.255| 1.738  | 0.0822 | *   |
|              | o_law/crime        | +0.412| 0.218| 1.890  | 0.0588 | *   |
|              | multi_answers      | +0.341| 0.024| 14.090 | 0.0000 | **** |
|              | t_who              | +0.230| 0.129| 1.778  | 0.0754 | *   |
|              | o_politics         | -0.208| 0.095| 2.177  | 0.0295 | **  |
|              | o_writing          | +0.192| 0.098| 1.955  | 0.0506 | *   |

Table 4: Influential features after filtering characteristics based on a $\chi^2$ test (Figure 1). Highly influential features ($p$-value < 0.1), both positive (blue) and negative (red). Higher number of *’s signals higher significance.

than evidence of absence: these are skewed datasets that have fewer than a quarter of the questions about women. It is difficult to make confident assessments on such small datasets—many demographic values were excluded because they appeared infrequently (or not at all). Improving the diversity of QA datasets can help us be more certain that QA systems do generalize and reflect the diverse human experience. Considering such shortcomings, Rodriguez et al. (2021) advocate improving evaluation by focusing on more important examples for ranking models; demographic properties could further refine more holistic evaluations.

A broader analysis beyond person entities would indeed be a natural extension of this work. Label propagation can expand the analysis beyond people: the Hershey-Chase experiment is associated with Alfred Hershey and Martha Chase, so it would—given the neighboring entities in the Wikipedia link graph—be 100% American, 50% male, and 50% female. Another direction for future work is accuracy under counterfactual perturbation: swapping real-world entities (in contrast with nonce entities in Li et al. (2020)) with different demographic values.

Nonetheless, particularly for professional fields, imbalances remain. The lack of representation in QA could cause us to think that things are better than they are because of Simpson’s paradox (Blyth, 1972): gender and profession are not independent! For example, in NQ, our accuracy on women is higher in part because of its tilt toward entertainment, and we cannot say much about women scientists. We therefore caution against interpreting strong model performance on existing QA datasets as evidence that the task is ‘solved’. Instead, future work must consider better dataset construction strategies and robustness of accuracy metrics to different subsets of available data, as well as unseen examples.

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Ethical Considerations

This work analyses demographic subsets across QA datasets based on Gender, Nationality and Profession. We believe the work makes a positive contribution to representation and diversity by pointing out the skewed distribution of existing QA datasets. To avoid noise being interpreted as signal given the lack of diversity in these datasets, we could not include various subgroups that we believe should have been part of this study: non-binary, intersectional groups (e.g., women scientists in NQ), people indigenous to subnational regions, etc. We believe increasing representation of all such groups in QA datasets would improve upon the status quo. We infer properties of mentions using Google Cloud-NL to link the entity in a QA example to an entry in the WikiDATA knowledge base to attribute gender, profession and nationality. We acknowledge that this is not foolproof and itself vulnerable to bias, although our small-scale accuracy evaluation did not reveal any concerning patterns.

All human annotations are provided by authors to verify entity-linkings and were fairly compensated.

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Appendix

A Entity collapses of demographic values

While mapping QA examples to person entities and values for their corresponding demographic characteristics (Section 2), we encountered many nearby values: ‘Poet’, ‘Writer’, ‘Author’. We collapse such values into a single label which we use for further analysis. This section enlists all the collapses that we encounter for determining nationality of people (Appendix A.1) and their professions (Appendix A.2).

A.1 Entity-collapses for Nationality values

**US:** kingdom of hawaii, united states, united states of america

**UK:** commonwealth of england, great britain, kingdom of england, kingdom of mercia, kingdom of scotland, kingdom of wessex, united kingdom, united kingdom of great britain and ireland

**Albania:** kingdom of albania

**Austria:** austrian empire, federal state of austria, first republic of austria

**Cyprus:** kingdom of cyprus, republic of cyprus, turkish republic of northern cyprus

**Denmark:** kingdom of denmark

**France:** kingdom of france

**Germany:** german confederation, german democratic republic, german empire, german reich, germany, kingdom of hanover, kingdom of prussia, kingdom of saxony, nazi germany, north german confederation, prussia, republic of german-austria, west germany

**Greece:** ancient greece, greece

**Hungary:** hungary, kingdom of hungary, people’s republic of hungary

**Ireland:** irish republic, kingdom of ireland

**Italy:** ancient rome, florence, holy roman empire, kingdom of italy, kingdom of sardinia

**Netherlands:** dutch republic, kingdom of the netherlands

**Poland:** kingdom of poland, poland

**Portugal:** kingdom of portugal

**Romania:** kingdom of romania, romania, socialist republic of romania

**Spain:** crown of castile, kingdom of aragon, kingdom of castile, kingdom of navarre, spain

**Yugoslavia:** federal republic of yugoslavia, kingdom of yugoslavia, socialist federal republic of yugoslavia, yugoslavia

**Iraq:** ba’athist iraq, iraq, kingdom of iraq, mandatory iraq, republic of iraq (1958–68)

**Israel:** israel, kingdom of israel, land of israel

**Russia:** russia, russian empire, russian soviet federative socialist republic, soviet union, tsardom of russia

**India:** british raj, delhi sultanate, dominion of india, india
China: china, people’s republic of china, republic of china (1912–1949)

Egypt: ancient egypt, egypt, kingdom of egypt, republic of egypt

A.2 Entity-collapses for Profession values

Writing: author, biographer, cartoonist, children’s writer, comedy writer, comics artist, comics writer, contributing editor, cookery writer, detective writer, diarist, editor, editorial columnist, essayist, fairy tales writer, grammarian, hymnwriter, journalist, lexicographer, librettist, linguist, literary, literary critic, literary editor, literary scholar, memoirist, newspaper editor, non-fiction writer, novelist, opinion journalist, philologist, photojournalist, physician writer, playwright, poet, poet lawyer, preface author, prosaist, religious writer, science fiction writer, science writer, scientific editor, screenwriter, short story writer, tragedy writer, travel writer, women letter writer, writer

Sports: amateur wrestler, american football coach, american football player, archer, artistic gymnast, association football manager, association football player, association football referee, athlete, athletics competitor, australian rules football player, badminton player, ballet dancer, ballet master, ballet pedagogue, baseball player, basketball coach, basketball player, biathlete, biathlon coach, boxer, bridge player, canadian football player, chess player, choreographer, coach, cricket umpire, cricketer, dancer, darts player, field hockey player, figure skater, figure skating choreographer, figure skating coach, formula one driver, gaelic football player, golfer, gridiron football player, gymnast, head coach, hurler, ice dancer, ice hockey coach, ice hockey player, jockey, judoka, lacrosse player, long-distance runner, marathon runner, marimba player, martial artist, middle-distance runner, mixed martial artist, motorcycle racer, poker player, polo player, pool player, professional wrestler, quidditch player, racing automobile driver, racing driver, rink hockey player, rugby league player, rugby player, rugby union coach, rugby union player, runner, short track speed skater, skateboarder, skeleton racer, snooker player, snowboarder, sport cyclist, sport shooter, sporting director, sports agent, sports commentator, sprinter, squash player, surfer, swimmer, table tennis player, taekwondo athlete, tennis coach, tennis player, thai boxer, track and field coach, viol player, volleyball player, water polo player

Music: bass guitar, bassist, blues musician, child singer, classical composer, classical guitarist, classical pianist, collector of folk music, composer, conductor, country musician, drummer, film score composer, ghost singer, guitar maker, guitarist, heavy metal singer, instrument maker, instrumentalist, jazz guitarist, jazz musician, jazz singer, keyboardist, lyricist, multi-instrumentalist, music arranger, music artist, music critic, music director, music interpreter, music pedagogue, music pedagogy, music producer, music publisher, music theorist, music video director, musical, musical instrument maker, musician, musicologist, opera composer, opera singer, optical instrument maker, organist, pianist, playback singer, professor of music composition, rapper, record producer, recording artist, rock drummer, rock musician, saxophonist, session musician, singer, singer-songwriter, songwriter, violinist

Fictional: fictional aviator, fictional businessperson, fictional character, fictional cowboy, fictional domestic worker, fictional firefighter, fictional journalist, fictional mass murderer, fictional pirate, fictional police officer, fictional politician, fictional schoolteacher, fictional scientist, fictional seaman, fictional
secretary, fictional soldier, fictional space traveller, fictional taxi driver, fictional vigilante, fictional waitperson, fictional writer

Politics: activist, ambassador, animal rights advocate, anti-vaccine activist, civil rights advocate, civil servant, climate activist, colonial administrator, consort, dictator, diplomat, drag queen, duke, emperor, feminist, foreign minister, government agent, governor, human rights activist, internet activist, khan, king, leader, lgbt rights activist, military commander, military leader, military officer, military personnel, military theorist, minister, monarch, peace activist, political activist, political philosopher, political scientist, political theorist, politician, president, prince, princess, protestant reformer, queen, queen consort, queen regnant, religious leader, revolutionary, ruler, secretary, social reformer, socialite, tribal chief

Artist: architect, artist, baker, blacksmith, car designer, chef, costume designer, design, designer, fashion designer, fashion photographer, fresco painter, furniture designer, game designer, glass artist, goldsmith, graffiti artist, graphic artist, graphic designer, house painter, illustrator, industrial designer, interior designer, jewellery designer, landscape architect, landscape painter, lighting designer, painter, photographer, postage stamp designer, printmaker, production designer, scientific illustrator, sculptor, sound designer, textile designer, type designer, typographer, visual artist

Film/tv: actor, character actor, child actor, documentary filmmaker, dub actor, factory owner, fashion model, film actor, film critic, film director, film editor, film producer, filmmaker, glamour model, line producer, model, pornographic actor, reality television participant, runway model, television actor, television director, television editor, television presenter, television producer, voice actor

Executive: bank manager, business executive, business magnate, businessperson, chief executive officer, entrepreneur, executive officer, executive producer, manager, real estate entrepreneur, talent manager

Stage: circus performer, comedian, entertainer, mine artist, musical theatre actor, stage actor, stand-up comedian, theater director

Law/crime: art thief, attorney at law, bank robber, canon law jurist, courtier, criminal, judge, jurist, lawyer, official, private investigator, robber, serial killer, spy, thief, war criminal

History: anthropologist, archaeologist, art historian, church historian, classical archaeologist, egyptologist, explorer, historian, historian of classical antiquity, historian of mathematics, historian of science, historian of the modern age, labor historian, legal historian, literary historian, military historian, music historian, paleoanthropologist, paleontologist, philosophy historian, polar explorer, scientific explorer

Science/tech: aerospace engineer, alchemist, anesthesiologist, artificial intelligence researcher, astrologer, astronaut, astronomer, astrophysicist, auto mechanic, bacteriologist, biochemist, biologist, botanist, bryologist, cardiologist, chemical engineer, chemist, chief engineer, civil engineer, climatologist, cognitive scientist, combat engineer, computer scientist, cosmoologist, crystallographer, earth scientist, ecologist, educational psychologist, electrical engineer, engineer, environmental scientist, epidemiologist,
ethnologist, ethologist, evolutionary biologist, geochemist, geographer, geologist, geophysicist, immunologist, industrial engineer, inventor, marine biologist, mathematician, mechanic, mechanical automaton engineer, mechanical engineer, meteorologist, microbiologist, mining engineer, naturalist, neurologist, neuroscientist, nuclear physicist, nurse, ontologist, ornithologist, patent inventor, pharmacologist, physician, physicist, psychologist, railroad engineer, railway engineer, research assistant, researcher, social psychologist, social scientist, sociologist, software engineer, space scientist, statistician, structural engineer, theoretical biologist, theoretical physicist, virologist, zoologist

**Polymath:** polymath

**Education:** academic, adjunct professor, associate professor, educator, head teacher, high school teacher, history teacher, lady margaret’s professor of divinity, pedagogue, professor, school teacher, sex educator, teacher, university teacher

**Economics:** economist

**Religion:** anglican priest, bible translator, bishop, catholic priest, christian monk, lay theologian, monk, pastor, pope, preacher, priest, theologian

**Military:** air force officer, aircraft pilot, commanding officer, fighter pilot, general officer, helicopter pilot, intelligence officer, naval officer, officer of the french navy, police officer, soldier, starship pilot, test pilot

**Translation:** translator

**Philosophy:** analytic philosopher, philosopher, philosopher of language,
B Logistic Regression features.

This section enlists a full set of features used for the logistic regression analysis after feature reduction, each with their coefficients, standard error, Wald Statistic and significance level in Table 5. We also describe the templates and the implementation details of the features using in our logistic regression analysis (Section 3.2) in Appendix B.1, and finally enlist some randomly sampled examples both from NQ and TriviaQA datasets in Appendix B.2 to show how multi_answers feature has disparate effects on them.

B.1 Implementation of Logistic Regression features

- **q_sim**: For closed-domain QA tasks like NQ and SQuAD, this feature measures (sim)ilarity between (q)uestion text and evidence sentence—the sentence from the evidence passage which contains the answer text—using Jaccard similarity over unigram tokens (Sugawara et al., 2018). Since we do not include SQuAD in our logistic regression analysis (Section 3.2), this feature is only relevant for NQ.

- **e_train_count**: This binary feature represents if distinct (e)ntities appearing in a QA example (through the approach described in Section 2) appears more than twice in the particular dataset’s training fold. We avoid logarithm here as even the log frequency for some commonly occurring entities exceeds the expected feature value range.

- **t_wh**\_A: This represents the features that captures the expected entity type of the answer: \( t_{\text{who}}, t_{\text{what}}, t_{\text{where}}, t_{\text{when}} \). Each binary feature captures if the particular “wh” word appears in the first ten (t)okens of the question text.\(^6\)

- **multi_entities**: For number of linked person-entities in a example as described in Section 2 as \( n \), this feature is \( \log_2(n) \). Hence, this feature is 0 for example with just one person entity.

- **multi_answers**: For number of gold-answers annotated in a example as \( n \), this feature is \( \log_2(n) \). Hence, this feature is 0 for example with just one answer.

- **g\_female**: Binary demographic feature signaling the presence of the (g)ender characterized by the feature. For instance, g_female signals if the question is about a female person.

- **o\_writer**: Binary demographic feature signaling the presence of the occupation (or profession) as characterized by the feature. For instance, o_writer signals if the question is about a writer.

B.2 Examples with multi_answers feature

In the Logistic Regression analysis (Section 3.2), we create two features: multi_answers and multi_entities. Former captures the presence of multiple gold answers to the question in a given example, while latter signals presence of multiple person entities — all in either the answers, the question text or the document title for a given example. While multi_entities has consistent negative co-relation with model correctness (Appendix B), multi_answers has a disparate effect. Though it signals towards incorrectly answered examples in NQ, it has a statistically significant positive correlation with model correctness for TriviaQA examples. Going through the examples, it reveals that TriviaQA uses multiple answers to give alternate formulations of an answer, which aids machine reading, while multiple NQ answers are often a sign of question ambiguity (Min et al., 2020).

To demonstrate that, we enlist here examples from development fold of both NQ (Appendix B.2.1) and TriviaQA (Appendix B.2.2) that have multiple gold answers.

B.2.1 NQ examples with multiple answers:

| Q: who said that which we call a rose | id: 8838716539218945006 |
| Who wrote the song if i were a boy | id: 9844452603979815006 |
| Who started the guinness book of world records | id: 6197052503812142206 |
| Who has won the most superbowls as a player | id: 6197052503812142206 |
| Who carried the us flag in the 2014 olympics | id: 6197052503812142206 |
| Who has the most superbowl rings as a player | id: 6197052503812142206 |

\(^6\)QB questions often start with “For 10 points, name this writer who...”
Table 5: Influential features revealed through Logistic Regression Analysis (Sec 3.2) over the demographic characteristics deemed significant through the χ² test (Figure 1). We report the highly influential features with significance of p-value < 0.1, both positive (blue) and negative (red), and bold the highly significant ones (p-value < 0.05). Number of * in the last column represents the significance level of that feature.
id: 846619474705624263
Q: who was running as vice president in 1984
A: Congresswoman Ferraro

A: Vice President George ...
Jews
A: Bill Clinton
A: Midi
A: John Adam Mc
A: Davros
A: 2001
A: Chainsmok
A: 10
A: Mayu
A: Jean
A: El
A: the Rock
A: Stock
A: Tale
A: Piz
A: Jeana
A: of Gaffi
A: Daya
A: Travis Tritt
A: -Kenny
A: Tim
A: Rogers
A: the Long
A: Ross
A: Fer
A: Ches
A: Kobe
A: Levy
A: Lo
A: Henry
A: Kim
A: Brown

A: who sang never gonna let you go
A: who sang what are we doing in love
A: who wrote cant get you out of my head lyrics
A: who were the two mathematicians that invented calculus
A: who invented the first home video security system
A: who sings somebody's watching me with michael jackson
A: Rockwell
A: Jimmy Jackson
A: who invented the printing press and in what year
A: who invented the first home video security system
A: who sings the song going to kansas city
A: who sings the song going to kansas city
A: who wrote he ain't heavy he's my brother lyrics
A: who were the twins that played for kentucky
A: who wrote the song going to kansas city
A: who invented the printing press and in what year
A: who invented the printing press and in what year
A: who developed a set of postulates to prove that specific microorganisms cause disease
A: who is hosting e live from the red carpet
A: who are the two mathematicians that invented calculus
A: who sang i'm never gonna let you go
A: who were the twins that played for kentucky
A: who was running as vice president in 1984
A: who wrote the song going to kansas city
A: who is hosting e live from the red carpet
A: who invented the first home video security system
A: who was running as vice president in 1984
Q: The 27 episodes of which sitcom featuring Julia McKenzie, Anton Rodgers and Ballard Berkley were first broadcast in the 1980s?
A: Rock Follies
A: Rock Follies of '77

Q: What is the name of the character played by Nicole Kidman in the film "Moulin Rouge"?
A: SATINE
A: SATINE

Q: Which 2009 film is a biopic of John Lennon?
A: Nowhere Boy
A: Nowhere Boy

Q: Which movie did Samuel Greg build to house workers at his nearby Quarry Bank Mill?
A: Styal
A: Styal

Q: What is the disease that Stephen Hawking has?
A: amyotrophic lateral sclerosis
A: amyotrophic lateral sclerosis

Q: Famous for "Die Welt als Wille und Vorstellung", Arthur Schopenhauer (1788-1860) was a German?
A: philosophers
A: philosophers

Q: Lieutenant General James Thomas Braidwell, who commanded the Light Brigade of the British Army during the Crimean War, was the 7th Earl of what?
A: cardigan
A: cardigan

Q: What is the nickname of the frontiersman Nathaniel Poe, played by Daniel Day Lewis, in the 1992 film "The Last of the Mohicans"?
A: Hawkeye
A: Hawkeye

Q: Who duetted with Syd Owen on the single "Better Believe It", which was released as part of the Children in Need appeal in 1995?
A: Patsy Palmer
A: Patsy Palmer

Q: What was Pete Sampress seeded when he won his first US Open?
A: 2
A: 2

Q: Who wrote the novels About A Boy, How To Be Good and High Fidelity?
A: Nick Hornby
A: Nick Hornby

Q: Who was the first woman to be seen on Channel 4? A: Carol Vorderman
A: Carol Vorderman

A: TREVOR

Q: Which actor played the part of Ross Poldark in the BBC's mid 1970's television series? A: Robin Ellis
A: Robin Ellis

Q: In 1995, Steffi Graf became the only tennis player to have won each of the four grand slam events how many times?
A: one thousand, nine hundred and eighty-two
A: one thousand, nine hundred and eighty-two

Q: Who was the defending champion when Martina Navratilova first won Wimbledon singles in 1978?
A: ANNE KLEEMANS
A: ANNE KLEEMANS

Q: In 1960, which London nightclub did Mark Birley name after his then wife?
A: PENITENTS
A: PENITENTS

Q: Which of Bob Dylan's songs begins "You got a lotta nerve/To say you are my friend. When I was down, you just stood there grinning"?
A: Don't Think Twice, It's All Right
A: Don't Think Twice, It's All Right

Q: On which river does Ipswich stand?
A:afür
A:afür

Q: How many times did Steffi Graf win the Ladies Singles at Wimbledon?
A: one thousand, nine hundred and forty-eight
A: one thousand, nine hundred and forty-eight

Q: What is the nickname of the frontiersman Nathaniel Poe, played by Daniel Day Lewis, in the 1992 film "The Last of the Mohicans"?
A: Hawkeye
A: Hawkeye

Q: What is the name of the character played by Nicole Kidman in the film "Moulin Rouge"?
A: SATINE
A: SATINE

Q: Which movie did Samuel Greg build to house workers at his nearby Quarry Bank Mill?
A: Styal
A: Styal

Q: What remake of a British science-fiction serial broadcast by BBC Television in the summer of 1953 was staged live by BBC Four in 2005 with actors Jason Flemyng, Mark Gatiss, Andrew Tiernan, Indira Varma, David Tennant and Adrian Bower? A: Quatermass
A: Quatermass

Q: In 1982, which London nightclub did Mark Birley name after his then wife?
A: PENITENTS
A: PENITENTS

Q: Which single by 'Leapy Lee' reached number two in the UK charts in 1968?
A: ROW'S	A: ROW'S

Q: What is the name of the character played by Nicole Kidman in the film "Moulin Rouge"?
A: SATINE
A: SATINE

Q: Who wrote the novels About A Boy, How To Be Good and High Fidelity?
A: Nick Hornby
A: Nick Hornby

Q: Which of Bob Dylan's songs begins "You got a lotta nerve/To say you are my friend. When I was down, you just stood there grinning"?
A: Don't Think Twice, It's All Right
A: Don't Think Twice, It's All Right

Q: On which river does Ipswich stand?
A:für
A:für

Q: How many times did Steffi Graf win the Ladies Singles at Wimbledon?
A: one thousand, nine hundred and forty-eight
A: one thousand, nine hundred and forty-eight

Q: What is the nickname of the frontiersman Nathaniel Poe, played by Daniel Day Lewis, in the 1992 film "The Last of the Mohicans"?
A: Hawkeye
A: Hawkeye

Q: What is the name of the character played by Nicole Kidman in the film "Moulin Rouge"?
A: SATINE
A: SATINE

Q: Which movie did Samuel Greg build to house workers at his nearby Quarry Bank Mill?
A: Styal
A: Styal

Q: What remake of a British science-fiction serial broadcast by BBC Television in the summer of 1953 was staged live by BBC Four in 2005 with actors Jason Flemyng, Mark Gatiss, Andrew Tiernan, Indira Varma, David Tennant and Adrian Bower? A: Quatermass
A: Quatermass
id: odql_10746
Q: Who wrote the 1951 novel 'The Caine Mutiny'?
A: HERMAN WOUK
A: Herman Wouk
id: bb_285
Q: Said to refer erroneously to the temperature at which book paper catches fire, the title of Ray Bradbury’s 1953 novel about a futuristic society in which reading books is illegal, is called 'Fahrenheit... what? 972; 451; 100; or 25?'
A: 451
A: four hundred and fifty-one
id: odql_7290
Q: Who was the driver of the limousine at the time of Diana Princess of Wales’ death?
A: HENRI PAUL
A: Henri Paul
id: odql_3476
Q: Which island in the Grenadines of St. Vincent was bought by Colin Tennant in 1958? Princess Margaret built a holiday home there in the 1960’s.
A: MUSTIQUE
A: Mustique
id: odql_5476
Q: Which pop star had the real name of Ernest Evans?
A: CHUBBY CHECKER
A: ‘CHUBBY CHECKER’
id: tc_980
Q: "Which supermodel said, "I look very scary in the mornings?"
A: We don’t wake up for less than $10,000 a day
A: Linda Evangelista