Thematic fit bits:
Annotation quality and quantity for event participant representation

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Abstract
Modeling thematic fit (a verb–argument compositional semantics task) currently requires a very large burden of data. We take a high-performing neural approach to modeling verb–argument fit, previously trained on a linguistically machine-annotated large corpus, and replace corpus layers with output from higher-quality taggers. Contrary to popular beliefs that, in the deep learning era, more data is as effective as higher quality annotation, we discover that higher annotation quality dramatically reduces our data requirement while demonstrating better supervised predicate-argument classification. But in applying the model to a psycholinguistic task outside the training objective, we saw only small gains in one of two thematic fit estimation tasks, and none in the other. We replicate previous studies while modifying certain role representation details, and set a new state-of-the-art in event modeling, using a fraction of the data.

1 Introduction
Is more data necessarily more effective than better annotation? Is it always cheaper just to obtain and use data with mid-quality annotation than improve annotation quality over a smaller dataset? Traditionally, to researchers grounded in linguistics, it seemed obvious that higher quality and richer annotation should be better. But with the advent of “Big Data” the common wisdom seem to have shifted toward more data; Deep Learning continued this trend (see examples in Section 1.1).

We re-examine these questions using two types of natural language processing (NLP) tasks: (1) supervised thematic role prediction and word prediction given a predicate and a role; and (2) psycholinguistic tasks outside the training objective: rating the thematic fit between a verb and its potential arguments. These tasks have a large body of work in computational linguistics (see section 1.2).

∗This work was done before first author joined Bloomberg.

We examine the trade-offs involved in training models designed to accomplish these tasks through modeling events and their participants in a large corpus. The trade-off we focus on is using more data with mediocre linguistic annotations versus little data with higher-quality annotations. For the former we replicate a PropBank-based model of Hong et al. (2018) using their training data, a large corpus with machine-predicted annotations of mediocre quality. For the latter we replace some annotation layers with equivalent layers generated by higher quality linguistic tools. We improve on this baseline by modifying how missing role information and unknown (out-of-vocabulary) roles are represented. We also look at the trade-offs in training models over increasingly richer, more fine-grained, but potentially sparser, semantic role annotation.

1.1 The conundrum of data
Our first goal is to revisit a widely held assumption in the NLP community: mediocre machine-predicted annotation yields at scale better (or equivalent) models than high quality annotations (manual or state-of-the-art machine-predicted), whose scale is much smaller, due to compute, cost, and time constraints. For example, McClosky et al. (2006) and Foster et al. (2007), inter alia, use self-training1 to improve syntactic parsing – as an alternative to manually annotating more data – in same or different domain/genre. Petrov et al. (2010) show that using 100k machine-predicted constituency parses to train a new dependency parser contributed the equivalent of 2k manually annotated parses. Manually annotating is slower and more expensive, but better by definition.

However, despite growing amounts of annotated and unannotated textual resources, a number of tasks involving traditional linguistic levels of representation remain a challenge, which degrades...
performance in various research areas and applications: artificial intelligence (AI), machine reading / knowledge graph population, chatbots and natural language understanding (NLU), as well as computational psycholinguistic modeling and computational linguistics.

1.2 Semantic modeling

Our second goal is to explore ways to improve semantic modeling and the representations used for this modeling. We use semantic modeling to refer to tasks at the intersection of NLP and psycholinguistics that have to do with representing and processing generalized event knowledge (Pustejovsky, 1991; Zarcone and Padó, 2011):

Semantic role labeling (SRL) is the task of annotating text according to semantic frames and their roles as defined in frameworks such as FrameNet, VerbNet, or PropBank (Baker et al., 1998; Schuler and Palmer, 2005; Palmer et al., 2005). For example, given ‘I cut the cake with...’ (1) ‘marzipan’ or (2) ‘a knife’, the role Instrument/A3-MNR is normally desired for (2) but not for (1).

Role filling: given a predicate (typically a verb) and a thematic role, what words or phrases would be most appropriate for that role? This task can be viewed as the complement of SRL (given the word or phrase, what is its role?).

(Role) selectional preference of the verb: what roles are more likely with this verb? E.g., ‘cut’: Agent/Arg0, Patient/Arg1, Instrument/Arg3-MNR.

Thematic fit: Given a predicate and a role (say, ‘cut’ + Instrument), how well would a speaker of a given language (here, English) find ‘knife’ or ‘spoon’ fitting to the given role? And by extension: given a subset of a predicate and arguments (optionally also modifiers), can we predict the typicality level of the most recently added member to the rest of the given subset? This is often an abstraction of sentence comprehension (in humans): our thematic fit estimation changes as we hear more of the uttered sentence (Amsel et al., 2015).

Indirect thematic fit estimation learning from SRL annotations has shown promising results (Hong et al., 2018; Tilk et al., 2016; Santus et al., 2017). Following Hong et al. (2018) and others, we consider only the arguments’ syntactic heads together with their semantic roles. Given a new role, predict the fitness level of all known words and use the score of the given filler in the full score distribution as a fitness rating. (We also look at the complement: given a new word, predict the fitness of each possible role). These predictions are scored relative to human judgments (see Section 2).

1.3 Contributions

Exploring the data requirements of modeling human semantic representations allows us to revisit the question of the inherent difficulty of semantic tasks: Does semantic processing simply require more annotated data to achieve high quality, or has it not been represented in a way conducive for computers to learn adequately?

We look into how annotation quality and quantity (both number of semantic frames and number of sentences) affect learning. We also explore annotation granularity, taking thematic role set granularity (number of roles in model) as a test case. We often see that modelers focus on only the two most frequent PropBank semantic arguments (Arg0 and Arg1), and ignore the rest, or lump the rest together under a catch-all tag. Similarly, they focus on only few modifiers (e.g., Tilk et al. (2016) and Hong et al. (2018) use 2 core roles and 3 modifiers). We therefore trained models with increasing numbers of thematic role types (the predicate, its core arguments, and often-optional, non-core arguments or modifiers), using the better taggers, parsers, and labelers, and observed changes in prediction quality.

To summarize our main contributions, we

1. test how quality of annotation affects supervised role/word prediction, as training set size increases. We show in small to large sizes that mediocre annotation method is not as useful as better quality annotation.
2. test how quality of annotation affects thematic fit estimation as an application of our models that is not part of the training objective. We show the quality increases with training size but surprisingly, variance is high even in larger sizes, leaving no clear winner annotation.
3. claim that the high variance of the (indirectly optimized for) thematic fit estimation makes it more difficult to interpret conclusions from previous studies that did not report it.
4. show new state-of-the-art results on role and word prediction, as well as thematic fit estimate correlations.
5. tease apart effects of quality and quantity; tease apart the number of training sentences from the number of training frames (the semantic frames annotated in these sentences).
6. test how annotation granularity (role set size) affects thematic fit (and role/word prediction)
7. provide a new, open-data, large lexical semantic (and syntactic) resource in English, revising and expanding the previously published RW-Eng (Sayeed et al., 2018).

2 Background and related work

2.1 Thematic fit norms

Thematic fit norms take the form of averaged human-rated plausibility scores for a verb, a noun, and a thematic role into which the noun is supposed to be slotted. For example, we would ask human raters how well does "sword" fit as an instrument role-filler of the verb "cut"? Thematic fit norms are a subset of semantic feature/property fit norms that pertain to verb-argument relations. Exploring thematic fit allows for exploring the structure of the human lexicon and in exploring generalizations about affordances and the relationship between world knowledge and compositional semantics.

An early example of collected thematic fit norms is introduced by McRae et al. (1998). Human raters were asked to judge the fit of particular nouns with particular verbs in given roles. These take the form of 7-point Likert scale judgements. These original plausibility judgements focused mainly on Agent-Patient roles. Later Ferretti et al. (2001) provided norms for Instrument and Location roles.

Padó (2007) and Padó et al. (2009) sought to develop a probabilistic model of thematic fit. In the process, they collected additional Agent-Patient norms for a limited, balanced subset of verb-noun pairs chosen by frequency in the Penn Treebank (Marcus et al., 1993). Together, in addition to later efforts focusing on verb polysemy (Greenberg et al., 2015), these collected norms form an empirical basis for modeling human semantic expectations, albeit limited to roles that are relatively frequent and easily understood by raters.

2.2 Distributional modeling of thematic fit

Early work in thematic fit modeling emphasized building partially or fully supervised corpus-based models (Padó and Lapata, 2007; Herdağdelen and Baroni, 2009). The question arises whether less task-specific, less supervised models can be used to model the semantic generalizations that would underpin a robust thematic fit model. Baroni and Lenci (2010) proposed the Distributional Memory (DM) approach, a very high-dimensional tensor space representation that memorizes the frequency of numerous syntactic relations between lexical items in a large corpus consisting of UkWaC (Ferraresi et al., 2008), the British National Corpus (Consortium et al., 2007, BNC), and Wikipedia.

Sayeed et al. (2016) applied the DM approach to relation features based in an early form of neural SRL tagger (Collobert et al., 2011, SENNA). This and Baroni and Lenci’s syntax-based features were combined synergistically to produce thematic fit correlation scores superior to the result of each individually. The DM models were constructed without any reference to the evaluation data and can be considered unsupervised in that sense. However, their reliance on matrix multiplications made them difficult to extend to evaluating multiple roles simultaneously due to sparsity. They are also difficult to parameterize for finding optimal models.

Tilk et al. (2016) and Hong et al. (2018) worked to supplant DM approaches with neural networks. Their models train "event" embeddings with a pre-selected roleset, representing an entire semantic frame as input. Some of the role “slots” can be left empty, allowing for a variable number of arguments to be tested. Hong et al. (2018) applied a two-task training objective (limited SRL and role-filler noun prediction) to train NN models that not only performed well on thematic fit ratings, but also on several additional semantic tasks (e.g., event similarity and multiple-role compositionality).

Sayeed et al. (2016), Tilk et al. (2016), and Hong et al. (2018) all depend on the "Rollenwechsel-English", aka “RW-eng” corpus (hereafter RE; Sayeed et al., 2018), and use almost all of the corpus to train their models. Our work builds on the work of Hong et al. (2018), but differs in role set implementation, some hyper-parameter settings, and minor other technical details. Our work also builds on RE and extends it with newer annotation layers. One of the things we test is whether the quantity of data used for these models is necessary to achieve those results, particularly on the thematic fit task.

3 Dataset

In order to explore the topics raised in Section 1, we used the above-mentioned large-scale RE corpus. It is annotated with a fast-but-outdated SRL tagger and syntactic parser. We added new annotation layers with higher quality, more modern taggers and parser (hereafter OA, "Our annotations"). We replicated baseline models on RE and trained new
models on OA, as detailed in Section 4.

3.1 Text and RE Annotations

The RE corpus (Sayeed et al., 2018) consists of the SENNA-derived SRL output over 78M sentences from 2.3M documents. The documents come from the BNC and ukWaC. SENNA extracts multiple predicates per sentence and, for each predicate, it identifies spans of text representing noun phrases that fill PropBank roles for that predicate. For every document, sentence, and predicate in that sentence, RE contains XML-formatted information on the corresponding SENNA output. In particular, it uses a series of head-finding heuristics (Sayeed et al., 2016) to identify the syntactic heads of the role-filling spans—typically noun phrases, which can contain complex constituents such as subordinate clauses, but the SRL role spans could also cover only fractions of syntactic constituents, hence the need for a heuristic beyond only using a parser.

3.2 Our Annotations (OA)

NLP often contains “pipelines” of serial annotation processes, such as: tokenization and morphological analysis (including lemmatization or stemming), syntactic parsing, and a final processing such as machine translation, NLU (for chatbots), and sometimes SRL. As mentioned in Section 1, until about ten years ago, a rule of thumb often held: better quality of intermediate processing results in better quality at the end, although improvements are not linear, and small intermediate gains do not always translate to gains at the end of the pipeline.

Here we set to test out the new rule-of-thumb of the last decade for the case of thematic role prediction, slot filling (word prediction), and thematic fit estimation. We replaced annotation layers from older tools with annotations based on more recent tools (see below), introducing a non-negligible improvement in intermediate annotation quality.

The first step in doing so is to determine a consistent tokenization schema across all annotation layers, as some taggers either expect a certain schema or apply their own even if input text is largely tokenized. We iteratively modified our tokenization schema to reduce token count mismatch between the new layers from over 20% of sentences to less than 1%. Once we reached this low mismatch ratio, we marked and excluded the fewer mismatched cases from our experiments.

We added the following new annotation layers:

- Lemmas by a newer morphological analyser: Morfette v0.4.4 (Chrupala et al., 2008; Chrupala, 2011), precompiled by Djamé Seddah, who included a transformed xtag lexicon (Seddah et al., 2013). Training was done on the Penn Treebank (Marcus et al., 1993), using the Collins split.

- Syntactic parses by a newer parser: spaCy 2.0.13 (Honnibal and Johnson, 2015; Honnibal and Montani, 2017). We forced spaCy to use our own tokenization instead of its own.

- Semantic frames by a newer SRL tagger: LSGN (He et al., 2018), an end-to-end BiLSTM-based SRL tagger using ElMo embeddings (Peters et al., 2018). It gets 86% F1 score on the CoNLL05 WSJ test set, compared to SENNA’s 75%. For each semantic frame, we aligned the spaCy parses to each argument span in order to find the syntactic head of the span, using a similar heuristic as in RE. We only used the heads for modeling (see Section 4). We align each token in the argument span across the various layers (surface word-form, Morfette lemma, spaCy lemma, spaCy entity (NER) tag, etc.)

3.3 Train / dev / test split

Of about 3500 files, few (less than 0.4%) were discarded due to processing issues, leaving us with 3490 files. Due to the fact that the corpus is comprised of more than one source, we assigned 16 files as the development set, chosen uniformly across the whole corpus and the 16 files immediately after each of these as the test set. The rest of the files were used as the full training set. Subsets of this training set were each chosen uniformly too, depending on the desired subset size, to emulate availability of smaller training sets. This split departs from Hong et al. (2018), which used the last 0.4% (14 files) as the test set, the immediately preceding 0.4% as the dev set, and the rest for training.

3.4 Additional test sets

We also tested our models on the above-mentioned thematic fit test sets, without optimizing on them:

- **Pado-all:** A human-rated thematic fit score dataset collected with psycholinguistic motivations,

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2 We thank Djamé Seddah for making it available to us.

3 https://spacy.io

4 Dev files: [217, 435, 651, 868, 1085, 1519, 1736, 1953, 2170, 2387, 2604, 2821, 3038, 3255, 3472]. Test files: [218, 436, 652, 869, 1086, 1302, 1520, 1737, 1954, 2171, 2388, 2605, 2822, 3039, 3256, 3473].
created by Padó (2007) and containing 414 verb-noun-role triplets, where every two triplets differ only in the role, one of \{Arg0, Arg1, Arg2\}.

McRae-all: A similar dataset with human scores, created by McRae et al. (1998), containing 1,444 such triplets, grouped in pairs similarly, but the roles are only \{Arg0, Arg1\}, and the words are less frequent (a harder task).

4 Experiments

4.1 Baseline Model Configuration

For our baseline (RE-based models), we used a multi-task residual network (ResNet; He et al., 2016; Jégou et al., 2010) model. Our implementation is similar to the best reported model in Hong et al. (2018), called ResRofa-MT, for ease of comparison. One task was predicting the role, given the word and one or more \{role,word\} pairs. A second task was predicting the word, given its role, and one or more \{role,word\} pairs. Aside from having different prediction layer per task, the tasks shared the same neural network (and parameters). Apart from software engineering differences, the most notable difference in our implementation is having two separate labels for missing role and unknown role instead of one for both. The former is used to mark the absence of a certain role from the annotated frame instance. The latter is used as a catch-all for sparser roles not explicitly represented. The baseline role set was comprised of PRD, Arg0, Arg1, ArgM-TMP, ArgM-LOC, ArgM-MNR: the predicate, PropBank’s arguments 0 and 1, and the temporal, location, and manner modifiers (and missing role and unknown role).

For faster training time, we used a batch size of 1024 samples (unless otherwise specified) with the risk of too coarse updates. We kept a simple setting of 0.1 learning rate and no decay. We applied the same vocabulary pruning to the top 50k most frequent lemma forms as Hong et al. (2018) did.

4.2 RE vs OA experiments

We trained and evaluated models in the above configuration with increasing training set size (see Section 3.3), measured in percentage of total number of available training sentences.

For each training set size, we trained few models on RE and same number of models on OA. We kept the same dev and test split throughout.

Table 1 shows that role prediction accuracy increases with training set size as expected and surpasses 90% at 1% of the training set for RE and already at 0.1% for OA. At 10% of the training, it reaches mid-90s for RE and high-90s for OA, with small further gains at 20%. The advantage of OA was kept throughout but decreased from over 5-6% (absolute) at 0.1% size to 3-4% at higher training set sizes. Word prediction accuracy followed similar trends, but OA–RE gaps there remained about 6% in all set sizes.

We also tested the models on two thematic fit tasks on which the models were not trained, using the additional test sets described in Section 3.4. Variance over multiple test sets described in Section 3.4. Variance over multiple test sets described in Section 3.4. Variance over multiple test sets described in Section 3.4. We report both the best- and last-epoch results for these tasks on the rightmost two columns of Table 1. We see OA advantage on Pado-max 10% and 20% but not at lower sizes. Pado-final results are mixed, particularly at 10%-training, as are the results on McRae (both last and best). We see clear training size effects on McRae(best+last), but not on Pado except in the smallest size.

The RE results on the 10% and 20% subsets are our closest replication of Hong et al. (2018), modulo the above-mentioned role representation.

4.3 Roleset Granularity (on OA)

Model design includes decisions about features and their granularity. Generally, fine-grained features provide sharper, more accurate distributions of underlying phenomena, but their values, especially at the distribution “tail”, suffer from higher sparsity, which may lead to difficulty in learning them well and hence lower performance overall. This tension between granularity and sparsity exists also for the case of role set granularity. Many studies have chosen the coarser side, using only few thematic roles. For example, Hong et al. (2018), which we take as our main baseline, use only 2 arguments and 3 modifiers, within the PropBank framework—in
Table 1: RE vs OA: model MTRFv4Res, train % out of 3490 text files, dev/test size = 16 text files each, batch=1024 unless specified.

| Name            | Role set               | Role acc. | Word acc. | Word acc. | Word acc. | Word acc. | Word acc. | Word acc. | Word acc. | Word acc. | Word acc. | Word acc. |
|-----------------|------------------------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|
| 2Args3Mods      | baseline               | **9653/9656** | .9393 / .9141 | .4765 / .4840 | .3705 / .3240 |
| 3Args3Mods      | +Arg2                  | .9595 / .9596 | .1544 / .1563 | .5056 / .5150 | .3340 / .3340 |
| 3Args4Mods      | +AM-MOD                | .9606 / .9609 | .1631 / .1661 | .4663 / .4928 | .3261 / .3373 |
| 3Args5Mods      | +AM-ADV                | .9513 / .9516 | .1665 / .1691 | .4838 / .5024 | .3381 / .3407 |
| 3Args6Mods      | +AM-DIS                | .9503 / .9510 | .1683 / .1712 | .4742 / .4851 | .3357 / .3370 |
| 3Args7Mods      | +AM-NEG                | .9506 / .9512 | .1742 / .1768 | .4808 / .4886 | .3357 / .3385 |
| all.args+mods   | all-roles              | .9450 / .9459 | **1783 / 1810** | .4833 / .5109 | .3205 / .3209 |
| 3Args3Mods      | +Arg2                  | .9595 / .9596 | .1544 / .1563 | .5056 / .5150 | .3340 / .3340 |
| 4Args3Mods      | +Arg3                  | .9580 / .9585 | .1557 / .1582 | .5007 / .5119 | .3365 / .3394 |
| 5Args3Mods      | +Arg4                  | .9574 / .9576 | .1559 / .1583 | .4901 / .5108 | .3473 / .3473 |
| 6Args3Mods      | +Arg5                  | .9577 / .9579 | .1560 / .1582 | .4925 / .5237 | .3166 / .3182 |

Table 2: Increasing role set granularity (OA): model MTRFv4Res, train size = 1% of 3490 text files, dev/test size = 16 text files each, batch=1024. Top half: adding next role in descending role frequency. Lower half: adding only arguments (skipping modifiers). In each half, the role set in each row is a superset of the previous row.

| Name            | Role set               | Role acc. | Word acc. | Word acc. | Word acc. | Word acc. | Word acc. |
|-----------------|------------------------|-----------|-----------|-----------|-----------|-----------|-----------|
| 2Args3Mods      | baseline               | **9653/9656** | .9393 / .9141 | .4765 / .4840 | .3705 / .3240 |
| 3Args3Mods      | +Arg2                  | .9595 / .9596 | .1544 / .1563 | .5056 / .5150 | .3340 / .3340 |
| 3Args4Mods      | +AM-MOD                | .9606 / .9609 | .1631 / .1661 | .4663 / .4928 | .3261 / .3373 |
| 3Args5Mods      | +AM-ADV                | .9513 / .9516 | .1665 / .1691 | .4838 / .5024 | .3381 / .3407 |
| 3Args6Mods      | +AM-DIS                | .9503 / .9510 | .1683 / .1712 | .4742 / .4851 | .3357 / .3370 |
| 3Args7Mods      | +AM-NEG                | .9506 / .9512 | .1742 / .1768 | .4808 / .4886 | .3357 / .3385 |
| all.args+mods   | all-roles              | .9450 / .9459 | **1783 / 1810** | .4833 / .5109 | .3205 / .3209 |
| 3Args3Mods      | +Arg2                  | .9595 / .9596 | .1544 / .1563 | .5056 / .5150 | .3340 / .3340 |
| 4Args3Mods      | +Arg3                  | .9580 / .9585 | .1557 / .1582 | .5007 / .5119 | .3365 / .3394 |
| 5Args3Mods      | +Arg4                  | .9574 / .9576 | .1559 / .1583 | .4901 / .5108 | .3473 / .3473 |
| 6Args3Mods      | +Arg5                  | .9577 / .9579 | .1560 / .1582 | .4925 / .5237 | .3166 / .3182 |

Table 3: SRL label counts in dev set

| Count | Label |
|-------|-------|
| 2,120,947 | ARG1 |
| 1,234,063 | PRD |
| 1,090,751 | ARG0 |
| 688,268  | ARG2 |
| 380,294  | ARGM-TMP |
| 257,056  | ARGM-MOD |
| 227,040  | ARGM-ADV |
| 220,502  | ARGM-MNR |
| 194,532  | ARGM-LOC |
| 95,724   | ARGM-DIS |
| 87,036   | ARGM-NEG |
| 68,156   | ARGM-PRP |
| 39,780   | ARGM-DIR |
| 35,938   | ARGM-ADV |
| 31,004   | ARG3 |
| 27,850   | ARGM-CAU |
| 22,092   | ARG4 |
| 18,254   | ARGM-EXT |
| 13,456   | ARGM-PRD |
| 9,108    | ARGM-LVB |
| 5,540    | ARGM-GOL |
| 3,826    | ARGM-COM |
| 3,460    | ARGM-PNC |
| 1,686    | ARGM-REC |
| 12       | ARG5 |

Note that now in Pado-all evaluations, Arg2 is no longer mapped to unknown-role. See Table 2. It turns out that while role set prediction accuracy slightly dropped, word prediction accuracy actually improved by more than 1%. Same trend held also for Pado-all (about 3% gain in Spearman’s correlation) and McRae-all (over 1%). This stands in contrast to preliminary experiments on RE. 10

Next down the role list, we added ArgM-MOD. While we saw a slight gain in word prediction accuracy, we saw a drop in Pado-all and perhaps a slight drop in McRae-all. However, adding ArgM-ADV resulted in a drop in role prediction but gains in the thematic fit tasks. Adding ArgM-DIS resulted in some drop on the thematic fit tasks, while adding ArgM-NEG yielded relative gains in word prediction and Pado-all. Adding all roles to the model (all.args+mods) yielded mixed results: a further small drop in role prediction (in fact, no model out-

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10Hong, personal communication.
performed the baseline on this task), a pronounced gain in word prediction (highest result even compared to Table 1), and lower scores on the thematic fit tasks compared to adding only Arg2.

Modifiers are often more freely optional, and are not considered core arguments of the semantic frame. We therefore also tested the effects of only adding core arguments to the baseline roleset (see bottom part of Table 2). Adding Arg3 resulted in no much change in any task, compared to +Arg2. Adding Arg4 yielded a gain on Pado-all last result (but not the maximal result). Adding Arg5 resulted in a clear drop on the thematic fit tasks, which is expected: Arg5 is very sparse, so its learnability is low, and roleset confusability is higher due to increased number of roles. However, we take differences on Pado-all and McRae-all with a grain of salt, given the above-mentioned high variability.

5 Discussion and Analysis

The advantage of OA-trained models over RE-trained models for role and word prediction in every training size undermines the NLP community’s widely-held working assumption that mediocre is always preferable at scale. It supports our hypothesis that sometimes “better is better” (better annotations yield better results), even at scale, compared to baselines of reasonable mediocrity. While we do not know if this holds also in the limit, this finding is worth keeping in mind even with today’s very large datasets.

To validate our claim that OA annotations are much better than RE, we randomly sampled 8 sentences, and counted the difference in number of frames, number of roles/arguments, and number of wrong role between the two datasets (Table 4). OA had a clear advantage over RE in identifying frames and roles, with almost no cases in which RE did better. This advantage held in both number of cases and number of sentences with offending cases (63–75%). Both RE and OA had few wrong roles, similar in number, with perhaps a slight advantage to RE (one case).\footnote{Note that for verification speed, we only verified correctness of OA’s Arg0, Arg1; the rest we assumed correct.} Due to the small sample size and evaluation method, we take the findings above as mainly qualitative, but still strongly supporting our assumption of OA advantage.

Was quality the only factor? Several aspects here: (a) better argument span and role prediction in LSGN in OA compared to SENNA in RE, together with (b) the greater quantity of predicted frames with LSGN, compounded by (c) better parsing quality of spaCy in OA compared to Malt in RE, and (d) Morfette’s better lemma analysis.

As for quantity, it turns out quantity may have also played a role: we compared the number of semantic frame annotations in the 10% training subset, and found out RE has less than 84% of OA’s, for same underlying sentences (Table 5). We call it frame quantity to tease it apart from sentence quantity: the number of (underlying) sentences used for training. Perhaps the better SRL and parser quality contributed both to the increase in number of frames as well as to the number of correctly extracted syntactic head words (one per argument, using better aligned parses).

Was the OA advantage mainly due to frame quantity? 1%-training OA outperforming 10%-training RE on role and word prediction, even though the former was trained on eighth of the number of frames (and tenth of the sentences), suggests otherwise. This trend repeated with 0.1%-training OA outperforming 1%-training RE on word prediction. Another takeaway from these comparisons is that higher quality annotations resulted in large savings in training sentence quantity for similar prediction quality.

How does our implementation fare compared to Hong et al. (2018)? Our OA maximal result on Pado-all (59.9% best single run, 56.2% averaged) outperforms their reported 53% with only 10% of their data. On McRae-all our maximal result (45.9% best single run, 43.9% averaged) outperforms their reported 42.5%, despite having less frequent predicate-argument combinations. Our OA outperform Hong et al.’s reported 94.7% role accuracy, even at 1% of their training data. We take it to be largely due to our difference in representation, mainly separating the catch-all unknown role from

| cases | missing frames | missing roles | wrong roles |
|-------|----------------|---------------|-------------|
| 10:0  | 21:1           | 3:4           |
| 5 (63%) | 7-1 (75%)  | 3-3 (0%)     |

Table 4: OA SRL advantage over RE over small sample

| data set   | previous (RE) | this (OA) |
|------------|---------------|-----------|
| training 10% | 16,889,581    | 20,151,313|
| dev        | 766,333       | 915,473   |
| test       | 767,325       | 919,365   |

Table 5: Number of frame annotations in RE vs. OA
missing role.

Could we have reached even higher results? Our model setting is on the simpler side with only two tasks, one of which is role prediction with accuracy approaching 100% (therefore, after a few iterations, largely only the other task affects the learning). More complex models or additional tasks (and/or modern word embeddings) are likely to do even better on the word prediction and the thematic fit tasks. However our focus in this work was not on creating the best model, but on exploring the effects of annotation quality and quantity up to large scale.

Did the effort of creating OA pay off also for the psycholinguistic task? We see a clear, but rather small gain in Pado-all on the larger subsets (10%, 20%). In McRae-all the gain is actually on the smaller subsets, and goes away on the larger ones. Therefore, we conclude that for improving indirectly supervised psycholinguistic tasks, the cost-effectiveness of this exercise is questionable, but it still suggests that progress can be made in resource-constrained environments through limited improvements in label accuracy.

As for annotation granularity, adding Arg2 to the baseline’s role set showed clear gains across the board (except perhaps in role prediction), which may seem surprising at first: (a) the role prediction task is now harder (larger role set) yet accuracy didn’t drop by much. This could be due to the increased thematic homogeneity in the catch-all role tag. (b) Word prediction (slot filling) was not expected to be affected, since the embeddings are not relearned in our setting. But gains may show if many words tend to assume only certain roles (e.g., be Arg2-centric). (c) Role prediction in Pado-all should have also been harder, therefore showing lower correlation scores. But recall that baseline scores are not directly comparable here because all roles but Arg0 and Arg1 were mapped to Arg2 for the evaluation of Pado-all, a mapping which was no longer needed once we added Arg2 to the role set. (d) gain in McRae-all is surprising at first because McRae-all only has Arg0 and Arg1 targets, so adding Arg2 could only distract from these targets. But recall we have a catch-all role, and adding Arg2 to the role set made the catch-all role distribution more focused, and therefore presumably less prone for mix-up with Arg0 and Arg1 – especially since McRae-all contains less frequent words, which makes them harder to learn.

Adding the next modifiers in order of descending frequency (top part of Table 2) yielded consistent monotonous gains in word prediction, with all-roles model, trained on 1% of the training set, performing even better than larger subset models in Table 1. This seems to support finer-grained representation. However, curiously, adding only core arguments (lower half of Table 2) did not make a noticeable difference on this task. Adding the next modifiers after Arg2 did not improve Pado-all, which is expected, since it only contains arguments 0-2. But the top result of +Arg4 on McRae-all is surprising: this test only has Arg0, Arg1 targets. We suspect this result is an outlier even given the high variance, but further investigation is in order.

6 Ethical considerations

This work depended on two corpora: the British National Corpus (BNC) and ukWaC. These are large corpora, with the problems that reliance on large corpora entail. ukWaC is a public web crawl large enough that it is not practical to completely account for all the data in the corpus.

The BNC is a curated corpus, but part of their transcribed conversations were recorded without prior consent of all recorded individuals. This is no longer an acceptable conduct in Great Britain and many other countries. Our annotated corpus (OA) clearly marks the source of each sentence, so those who wish to exclude BNC data can easily do so.

A matter of concern is that the models are making generalizations about predicate-argument relation typicality based on the perceptions of only a part of the world’s population. Whether there is anything "universal" about them is a complex question, but they should be seen in that light: as representing the part of the human species that produced the training data.

Insofar as future work keeps that in mind, we believe there to be minimal scope for direct misuse of our results.

7 Conclusions and Future Work

We set out to test the NLP community’s widely-held assumption that mediocre linguistic annotation at scale is as good as better annotation. We saw that models trained on better lemmas, syntactic parses, and SRL tags (our OA) did better than the baseline (RE) using older technology at all training set sizes, and even at scale – on both (directly supervised) role and word prediction. We also saw “training dataset savings” potential: training on smaller sets
with better annotations yielded sometimes better results than training on datasets with less advanced annotations that were several times larger in size. To better understand that, we teased apart contributions of annotation quality and quantity, and their interplay. We further teased apart sentence quantity from frame quantity.

We saw a high variance in thematic fit estimation, to the point where in one task (Pado-all) OA advantages over RE only showed in larger training set sizes, while in another task (McRae-all) no advantages were seen. Given the small-to-no gains in these tasks relative to RE, the cost-effectiveness of re-annotating with better tools is questionable for the indirect supervision setting.

We saw all tasks benefited from increasing the training sentence set size, at least until 10% of our large corpus (except perhaps Pado-all beyond 1%). Future work should check if larger sizes can yield even better results. Even at 10% of the training, our OA model set a new record in indirectly supervised thematic fit estimation on Pado-all, and at 20% a new record also on McRae-all (both RE, OA).

We also saw that refining the semantic role set granularity helps in thematic fit tasks (and word prediction). On Pado-all, best results were achieved already by adding Arg2, but surprisingly on McRae-all by adding Arg2-4. Adding all roles yielded best results on word prediction. These are novel results.

Last, but not least, we introduced a new open-data annotated corpus\footnote{Available for download at github.com/yuvalmarton/RW-Eng-v2-beta-src} on the way to finding answers the questions above. We believe this new corpus will be useful to the NLP community beyond our reported experiments. Future work involves studies with existing and new annotation layers, e.g., combining RE+OA parses, RE+OA SRL tags, and replicating these experiments with various word embeddings and different network architectures. Future work should also explore different optimization objectives or additional tasks in the multi-task setting, since role prediction seems too easy (reaches accuracy in high 90s early on), while the word prediction objective may be too hard, although the latter can be ameliorated with better word embeddings and a loss function based on the vector distance between predicted and target words. We also plan to add new thematic fit tasks with multiple simultaneous role-fillers (Bicknell et al., 2010; Vassallo et al., 2018).

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