Weak Supervision for Learning Discourse Structure

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Abstract

This paper provides a detailed comparison of a data programming approach with (i) off-the-shelf, state-of-the-art deep learning architectures that optimize their representations (BERT) and (ii) handcrafted-feature approaches previously used in the discourse analysis literature. We compare these approaches on the task of learning discourse structure for multi-party dialogue. The data programming paradigm offered by the Snorkel framework allows a user to label training data using expert-composed heuristics, which are then transformed via the “generative step” into probability distributions of the class labels given the data. We show that the generative model produced from these heuristics outperforms both deep learning architectures as well as more traditional ML approaches when learning discourse structure by up to 20 points of F1 score; it even outperforms the combination of generative and discriminative approaches that are the foundation of the Snorkel framework. We also implement several strategies for “decoding” our generative model output that improve our results. We conclude that weak supervision methods hold great promise as a means for creating and improving data sets for discourse structure.

1 Introduction

In this paper, we investigate and demonstrate the potential of a weak supervision, data programming approach (Ratner et al., 2016) to the task of learning discourse structure for multi-party dialogue. We offer a detailed comparison of our data programming approach with (i) off-the-shelf, state-of-the-art deep learning architectures that optimize their representations (BERT) and (ii) handcrafted-feature approaches previously used in the discourse analysis literature. Our data programming paradigm exploits the Snorkel framework that allows a user to label training data using expert-composed heuristics, which are then transformed via the “generative step” into probability distributions of the class labels given the data. We show that the generative model produced from these heuristics outperforms both deep learning architectures as well as more traditional ML approaches when learning discourse structure by up to 20 points of F1 score; it even outperforms the combination of generative and discriminative approaches that are the foundation of the Snorkel framework. We also implement several strategies for “decoding” our generative model output that improve our results. We conclude that weak supervision methods hold great promise as a means for creating and improving data sets for discourse structure.

2 State of the Art

Discourse structures for texts represent causal, topical, argumentative information through what are called coherence relations. For dialogues with multiple interlocutors, extraction of their discourse structures provides useful semantic infor-

\textsuperscript{1}https://www.irit.fr/STAC/
mation to the “downstream” models used, for example, in the production of intelligent meeting managers or the analysis of user interactions in online fora. However, despite considerable efforts to retrieve discourse structures automatically (Fisher and Roark, 2007; Duverle and Prendinger, 2009; Li et al., 2014; Joty et al., 2013; Ji and Eisenstein, 2014; Yoshida et al., 2014; Li et al., 2014; Surdeanu et al., 2015), we are still a long way from usable discourse models, especially for dialogue. Standard supervised models struggle to capture the sparse attachments, even when relatively large annotated corpora are available. In addition, the annotation process is time consuming and often fraught with errors and disagreements, even among expert annotators. This motivated us to explore the data programming approach that exploits expert linguistic knowledge in a more compact and consistent rule based form.

Given our interest in the analysis of multi-party dialogues, we used the STAC corpus of multi-party chats, an initial version of which is described in (Afantenos et al., 2015; Perret et al., 2016). In all versions of this corpus, dialogue structures are directed acyclical graphs (DAGs) formed according to SDRT\(^2\) (Asher and Lascarides, 2003; Asher et al., 2016). An SDRT discourse structure is a graph, \(⟨V, E_1, E_2, ℓ, \text{Last}⟩\), where: \(V\) is a set of nodes or Discourse Units (DUs); \(E_1 \subseteq V^2\) is a set of edges between DUs representing coherence relations; \(E_2 \subseteq V^2\) represents a dependency relation between DUs; \(ℓ: E_1 \to R\) is a labeling function that assigns a semantic type to an edge in \(E_1\) from a set \(R\) of discourse relation types, and \(\text{Last}\) is a designated element of \(V\) giving the last DU relative to textual or temporal order. \(E_2\) is used to represent Complex Discourse Units (CDUs), which are clusters of two or more DUs connected as an ensemble to other DUs in the graph. As learning this type of recursive structure presents difficulties beyond the scope of this paper, we followed a “flattening” strategy similar to (Muller et al., 2012) to remove CDUs. This process yields a set \(V^*\), which is \(V\) without CDUs, and a set \(E^*_1\), a flattened version of \(E_1\).

Building these structures typically requires three steps: (i) segmenting the text into the basic units of the discourse, typically clauses - these are EDUs or Elementary Discourse Units; these, together with CDUs, form the set of nodes \(V\) in the graph; (ii) predicting the attachments between DUs, i.e. to identify the elements in \(E_1\); (iii) predicting the semantic type of the edge in \(E_1\). This paper focuses on step (ii). Our dialogue structures are thus of the form \(⟨V^*, E^*_1, \text{Last}⟩\). Step (ii) is a difficult problem for automatic processing because attachments are theoretically possible between any two DUs in a dialogue or text, and often graphs include long-distance relations. Muller et al. (2012) is the first paper we know of that focuses on the discourse parsing attachment problem, albeit for monologue. It targeted a restricted version of an SDRT graph and trains a simple MaxEnt algorithm to produce probability distributions over pairs of EDUs, what we call a “local model” with a positive F1 attachment score of 0.635. They further applied global decoding constraints to produce a slight improvement in attachment scores (these are discussed in more detail in Section 5). Afantenos et al. (2015) used a similar strategy for dialogue on an early version of the STAC corpus. Perret et al. (2016) targeted a more elaborate approximation of SDRT graphs on the same version of the STAC corpus and reported a local model F1 attachment of 0.483. They then used Integer Linear Programming (ILP) to encode global decoding constraints particular to SDRT to improve the F1 attachment score to 0.689.

Having sketched recent progress in discourse parsing, we briefly turn to the state of the art concerning data programming. Ratner et al. (2016) introduced the data programming paradigm, along with a framework, Snorkel (Ratner et al., 2017), which uses a weak supervision method (Zhou, 2017), to apply labels to large data sets by way of heuristic labeling functions that can access distant, disparate knowledge sources. These labels are then used to train classic data-hungry machine learning (ML) algorithms. The crucial step in the data programming process uses a generative model to unify the noisy labels by generating a probability distribution for all labels for each data point. This set of probabilities replaces the ground-truth labels in a standard discriminative model outfitted with a noise-aware loss function and trained on a sufficiently large data set.

3 The STAC Annotated Corpus

3.1 Overview

While earlier versions only included linguistic moves by players, STAC now contains in addi-

\(^2\)Segmented Discourse Representation Theory
tion a multimodal corpus of multi-party chats be-
tween players of an online game (Asher et al.,
2016; Hunter et al., 2018). It includes 2,593 di-
alogues (each with a weakly connected DAG dis-
course structure), 12,588 “linguistic” DUs, 31,811
“non-linguistic” DUs and 31,251 semantic rela-
tions. A dialogue begins at the beginning of a
player’s turn, and ends at the end of that player’s
turn. In the interim, players can bargain with each
other or make spontaneous conversation. These
player utterances are the “linguistic” turns. In ad-
dition the corpus contains information given visu-
ally in the game interface but transcribed in the
corpus into Server or interface messages, “non-
linguistic” turns (Hunter et al., 2018). All turns
are segmented into DUs, and these units are then
connected by semantic relations.

Each dialogue represents a complete conversa-
tion. There are typically many such conversations,
each beginning with a non-linguistic turn in which
a player is designated to begin negotiations (see
Figure 1). The dialogues end when this player per-
forms a non-linguistic action that signals the end
of their turn. The dialogues are the units on which
we build a complete discourse structure.

The STAC multimodal corpus is divided into a
development, train and test set. The development
and test sets are each 10% of the total size of the
corpus.

To compare our approach to earlier efforts, we
also used the corpus from (Perret et al., 2016).
This corpus was also useful to check for over fit-
ting of our Generative model developed on the
multi-modal data. The corpus from (Perret et al.,
2016) is an early version of a “linguistic only”
version of the STAC corpus. It contains no non-
linguistic DUs, unlike the STAC multimodal cor-

3 There is also on the STAC website an updated linguis-
tic only version of the STAC corpus. It has 1,091 dialogues,
11,961 linguistic only DUs and 10,191 semantic relations.
We have not reported results on that data set here. The dataset
from (Perret et al., 2016) is similar to our linguistic only
STAC corpus but is still substantially different and degraded
in quality. Asher et al. (2016) report significant error rates
in annotation on the earlier versions of the STAC corpus and
that the current linguistic only corpus of STAC offers an
improvement over the (Perret et al., 2016) corpus.

ries were obviously not a correct representation
of what was going on in the game at the relevant
point.

3.2 Data Preparation
To concentrate on the attachment task, we imple-
mented the following simplifying measures on the
STAC corpus:

1. Roughly 56% of the dialogues in the corpus
contain only non-linguistic DUs. The dis-
course structure of these dialogues is more
regular and thus less challenging; so we ig-
nore these dialogues for our prediction task.

2. 98% of the discourse relations in our devel-
opment corpus span 10 DUs or less. To re-
duce class imbalance, we restricted the rela-
tions we consider to a distance of \( \leq 10 \).

3. Following (Muller et al., 2012; Perret et al.,
2016) we “flatten” CDUs by connecting all
relations incoming or outgoing from a CDU
to the “head” of the CDU, or its first DU.

The STAC corpus as we use it in our learning ex-
periments thus includes 1,130 dialogues, 13,734
linguistic DUs, 18,767 non-linguistic DUs and
22,098 semantic relations.

We also performed these operations on our ver-
sion of the linguistic only corpus used by (Perret
et al., 2016).

4 Data Programming Experiments
4.1 Candidates and Labeling Functions
The Snorkel implementation of the data program-
m ing paradigm inspired our weak supervision ap-
proach. We first identified and extracted candi-
dates from the data, and then wrote a set of la-
beling functions (LFs) to apply to the candidates
while only consulting the development set, the
10% of the STAC corpus set aside to develop and
test our LFs. We treated the training set (80% of
the corpus) as unseen/unlabeled data to which we
applied the finished LFs and the models. The last
10% of the STAC corpus was reserved as a final
test set.

Candidates are the units of data for which labels
are predicted. For this study, the candidates are all
DU pairs which could possibly be connected by a
semantic relation. We use our own method to cre-
cate candidates from the DUs culled from the texts
of the dialogues, making sure to limit the pairs to
those that occur in the same dialogues. We also ruled out the possibility of backwards relations between two DUs which have different speakers: it is linguistically impossible for a speaker of, say, an assertion \(d_1\) at time \(t_1\) to answer a question \(d_2\), asked by a different speaker at time \(t_2 > t_1\), i.e. before \(d_2\) was asked. That is, we include \((d_1, d_2)\) in our candidates but rule out \((d_2, d_1)\).

LFs are expert-composed functions that make an attachment prediction for a given candidate: each LF returns a 1, a 0 or a -1 (“attached”/“do not know”/“not attached”) for each candidate. However, each of our LFs is written and evaluated with a specific relation type Result, Question-answer-pair (QAP), Continuation, Sequence, Acknowledgement, Conditional, Contrast, Elaboration and Comment in mind. In this way, LFs leverage a kind of type-related information, which makes sense from an empirical perspective as well as an epistemological one. An attachment decision concerning two DUs is tightly linked to the type of relation relating the DUs: when an annotator decides that two DUs are attached, he or she does so with some knowledge of what type of relation attaches them.

LFs also exploit information about the DUs’ linguistic or non-linguistic status, the dialogue acts they express, their lexical content, grammatical category and speaker, and the distance between them—features also used in supervised learning methods (Perret et al., 2016; Afantenos et al., 2015; Muller et al., 2012). Finally, we fix the order in which each LF “sees” the candidates such that it considers adjacent DUs before distant DUs. This allows LFs to exploit information about previously predicted attachments and dialogue history in new predictions. Our rule set and their description are available here: https://tizirinagh.github.io/acl2019/. Figure 2 gives an example of a labeling function that we used.

4.2 The Generative Model

Once the LFs are applied to all the candidates, we have a matrix of labels (\(\overline{x}\)) given by each LF \(\Lambda\) for each candidate. The generative model, GEN, as specified in (1), provides a general distribution of marginal probabilities relative to n accuracy dependencies \(\phi_j(\Lambda_i, y_i)\) for an LF \(\lambda_j\) with respect inputs \(x_i\), the LF’s outputs on \(i\) \(\Lambda_{ij}\) and true labels.

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Figure 1: A dialogue from the STAC multimodal corpus featuring player (‘linguistic’) turns and Server/UI (‘non-linguistic’) turns. There are four instances of Result relations, shown in green. Result connects a cause to its effect, i.e., the main eventuality of the first argument is understood to cause the eventuality given by the second.

Figure 2: Glosses of two rules that are meant to capture the Result relations when applied to the candidates as pulled from the corpus, exemplified in Figure 1. Although the rules are written to capture specific relation types between segments, they return 1/0 for attached/not attached.
\[ y_i \] that depend on parameters \( \theta_j \) where:

\[ \phi_j(A_i, y_i) := y_iA_{ij} \]

\[ p_\theta(A, Y) \propto \exp\left(\sum_{i=1}^{m} \sum_{j=1}^{n} \theta_j \phi_j(A_i, y_i)\right) \tag{1} \]

The parameters are estimated by minimizing the negative log marginal likelihood of the output of an observed matrix \( A \) as in (2).

\[ \arg\min_\theta - \log \sum_{Y} p_\theta(A, Y) \tag{2} \]

GEN does not have access to the gold labels on the Training set but uses the Training set as unlabelled data. So in this model, the true class labels \( y_i \) are latent variables that generate the labeling function outputs, which are estimated via Gibbs sampling over the Training set (80% of the STAC corpus), after it has been labeled by the LFs. The objective in (2) is then optimized by interleaving stochastic gradient descent steps with Gibbs sampling ones. For each candidate, GEN thus uses the accuracy measures for the LFs in (1) to assign marginal probabilities that two DUs are attached.

GEN estimates the accuracy of each LF, a marginal probability for each label, and consequently a probability for positive attachment. In this model, the true class labels \( y_i \) are latent variables that generate the labeling function outputs. The model in (1) presupposes that the LFs are independent, but this assumption does not always hold: one LF might be a variation of another or they might depend on a common source of information (Mintz et al., 2009). If we don’t take these dependencies into account, we risk assigning incorrect accuracies to the LFs. Snorkel provides a more complex model that automatically calculates the dependencies between LFs and marginal probabilities which we use for the generative step (Bach et al., 2017). The higher order dependencies significantly improved the generative model’s results on the full STAC corpus (see Table 1).

When we obtain the results from the generative model GEN, we choose on the development corpus a threshold to apply to these marginals by calculating the threshold that gives us the best F1 score.

### 4.3 Discriminative Model

The standard Snorkel approach inputs the marginal probabilities from the generative step directly into a discriminative model, which is trained on those probabilities using a noise-aware loss function (Ratner et al., 2016). Ideally, this step generalizes the LFs by augmenting the feature representation - from, say, dozens of LFs to a high dimensional feature space - and allows the model to predict labels for more new data. Thus the precision potentially lost in the generalization is offset by a larger increase in recall.

We tested three discriminative models in our study. Each one was trained on the gold labeled data in the Training set of the STAC corpus. First we tried a single layer BI-LSTM with 300 neurons, which takes as input 100 dimensional embeddings for the text of each DU in the candidate pair. We concatenated the outputs of the BI-LSTM and fed them to a simple perceptron with one hidden layer and Rectified Linear Unit.
Table 1: Evaluations of attachment on Dev set with and without higher order dependencies.

| Generative Model on dev set | Precision | Recall | F1 score | Accuracy |
|-----------------------------|-----------|--------|----------|----------|
| Without higher order dependencies | 0.45 | 0.70 | 0.55 | 0.87 |
| With higher order dependencies | 0.68 | 0.67 | 0.67 | 0.92 |

(ReLU) activation (Hahnloser et al., 2000; Jarrett et al., 2009; Nair and Hinton, 2010) and optimized with Adam (Kingma and Ba, 2014). Given that our data is extremely unbalanced in favor of the “unattached” class (“attached” candidates are roughly 13% of the candidates on the development set), we also implemented a class-balancing method inspired by (King and Zeng, 2001) which maps class indices to weight values used for weighting the loss function during training.

We also implemented BERT (Devlin et al., 2018)’s sequence classification model (source code on the link below4) with 10 training epochs and all default parameters otherwise. BERT, the Bidirectional Encoder Representations from Transformers, is a text encoder pre-trained using language models where the system has to guess a missing word or word piece removed at random from the text. Originally designed for automatic translation tasks, BERT uses bi-directional self-attention to produce the encodings and performs at the state of the art on many textual classification tasks.

In order to use these methods, we had to binarize the marginal probabilities before moving to the discriminative step, using a threshold of \( p > .85 \) as explained in Section 4.2. Though this marks a departure from the standard Snorkel approach, we found that our discriminative model results were higher when the marginals were binarized and when the class re-balancing was used, albeit much lower than expected overall.

Finally, to facilitate comparison with earlier work, we also implemented a local model, LogReg* as mentioned in the following of the paper, that used marginal probabilities together with handcrafted features (the feature set used in (Afantenos et al., 2015) listed in their Table 2) and a Logistic Regression classifier.

5 Decoding

A set of highly accurate predictions for individual candidates does not necessarily lead to accurate discourse structures; for instance, without global structural constraints, GEN and local models may not yield the directed acyclic graphs (DAGs), required by SDRT. As in previous work (Muller et al., 2012; Afantenos et al., 2015; Perret et al., 2016), we use the Maximum Spanning Tree (MST) algorithm, and a variation thereof, to ensure that the dialogue structures predicted conform to some more general structural principle. We implemented the Chu-Liu-Edmonds algorithm (Chu, 1965; Edmonds, 1967), an efficient method of finding the highest-scoring non-projective tree in a directed graph, as described in Jurafsky and Martin5. The algorithm greedily selects the relations with the highest probabilities from the dependency graphs produced by the local model, then removes any cycles. The result is a tree structure with one incoming relation per node. In cases of nodes with multiple equiprobable incoming relations, the algorithm takes whichever relation it sees first.

Since SDRT structures can contain nodes with multiple incoming relations, i.e. are not always tree-like, we altered the MST algorithm in the manner of (Muller et al., 2012; Afantenos et al., 2015; Perret et al., 2016), forcing the MST to include all high-probability incoming relations which do not create cycles. This produces MS-DAG structures which are in principle more faithful to SDRT. In addition, since discourse attachments in general follow an inverse power law (many short-distance attachments and fewer long-distance attachments), we implemented two MST/MS-DAG variants that always choose the shortest relation among multiple high-probability relations (MST/short and MS-DAG/short).

6 Results and Analysis

We set out to test the performance of combinations of generative and discriminative models along the

4Link to BERT sequence classification model code: https://github.com/huggingface/pytorch-pretrained-BERT/blob/master/examples/run_classifier.py

5https://web.stanford.edu/~jurafsky/slp3/13.pdf
lines of the data programming paradigm on the

task of dialogue structure prediction in order to au-
tomatically generate SDRT corpus data. While our
results were consistent with what data program-
ming promises—more data with accuracy com-
parable if not slightly below that of hand-labeled
data—our most surprising and interesting result
was the performance of the generative model on
its own. As seen in Table 2 on STAC test data,
GEN dramatically outperformed our deep learn-
ing baselines—BiLSTM, BERT, and BERT + Lo-
gReg* architectures on gold labels—as well as the
LAST baseline, which attaches every DU in a di-
ologue to the DU directly preceding it. In addi-
tion, stand alone GEN also outperformed all the
coupled Snorkel models, in which GEN is com-
bined with an added discriminative step, by up
to a 30 point improvement in F1 score (GEN vs.
GEN+BiLSTM). We did not expect this, given
that adding a discriminative model in Snorkel is
meant to generalize, and hence improve, what
GEN learns.

Critical to this success was the inclusion of
higher order dependencies in GEN and the fact
that our LFs exploited contextual information
about the DUs that was unavailable to the deep
learning models or even the handcrafted feature
model. GEN beats all competitors in terms of F1
score while taking a fraction of the annotated data
to develop and train the model, showing the power
and promise of the generative model.

One might wonder whether GEN and discrim-
inative models are directly comparable. Gener-
ative machine learning algorithms learn the joint
probability of X and Y, whereas discriminative
algorithms learn the conditional probability of Y
given X. Nevertheless, when we exploit the gener-
ative model we are trying to find the Y for which
P(X \wedge Y) is maximized. In effect we are produc-
ing, though not learning, a conditional probabil-
ity. So it makes sense to compare our generative
model’s output with that of other, discriminative
machine learning approaches.

We also got surprising results concerning the
supervised model benchmarks. Table 2 shows that
LogReg* was the best supervised learning method
on the STAC data in terms of producing local mod-
els. This is evidence that hand crafted features
capturing non local information about a DU’s con-
texts do better than all purpose contextual encod-
ings from neural nets at least on this task. We
also implemented BERT+LogReg*, a learning al-
gorithm that uses BERT’s encodings together with
a Logistic Regression classifier trained on STAC’s
gold data with handcrafted features from (Afan-
tenos et al., 2015) and used in (Perret et al., 2016).
BERT+LogReg* outputs a local model that im-
proves upon BERT’s local model, but it did not do
as well as LogReg* on its own (let alone GEN),
suggesting that BERT’s encodings actually inter-
fered with the correct predictions.

We also investigated GEN coupled with various
discriminative models to test the standard Snorkel.
As we remarked above, we found that binariz-
ing GEN’s output improved the performance of
the coupled discriminative model, so Table 2 only
reports scores for various GEN-coupled discrim-
inative models that take the binarized GEN pre-
dictions as input. In keeping with our analysis
of the supervised benchmarks, we found that the
best discriminative model to couple with GEN in
the Snorkel architecture was LogReg*, far outper-
forming GEN with either a BiLSTM or BERT on
the STAC test set. Its results were only slightly
less good than those of stand alone GEN.

To further investigate comparisons between dif-
ferent architectures for solving the attachment
problem, we compared various local models ex-
tended with the MS-DAG decoding algorithm dis-
cussed in Section 5, giving the global results
shown in the righthand columns of Tables 3 and
4. With MS-DAG added, GEN continued to out-
perform all other approaches on STAC data. In
Table 5, we experimented with adding all decod-
ing algorithms to the local GEN result. This gave a
boost in F1 score—2 points with classic MST and
MS-DAG and 4 points with the variants favoring
relation instances with shorter attachments.

It is not surprising that MST improves the GEN
results, since it eliminates some of the false pos-
tive relations that pass the generative threshold
and includes some of the false negative relations
that fall below the threshold. The general inverse
power law distribution of discourse attachments
explains the good performance of the MST short-
est link variant. GEN + “MST-short” has the high-
est attachment score of all approaches to the prob-
lem of attachment in the literature (Morey et al.,
2018), though we are cautious in comparing scores
for systems applied to different corpora.

Finally, we wanted to see how GEN and our
other models fared on our version of the (Perret
Table 2: Evaluations of weakly supervised (Snorkel and stand alone GEN) and supervised approaches on STAC data.

| Supervised Baselines | Precision | Recall | F1 Score | Accuracy |
|----------------------|-----------|--------|----------|----------|
| LAST                 | 0.54      | 0.55   | 0.55     | 0.84     |
| BiLSTM on Gold labels| 0.33      | 0.80   | 0.47     | 0.75     |
| BERT on Gold labels  | 0.56      | 0.48   | 0.52     | 0.88     |
| LogReg* on Gold labels| 0.73     | 0.52   | 0.61     | 0.91     |
| BERT+LogReg* on Gold labels | 0.59 | 0.49 | 0.53 | 0.89 |

| Snorkel Pipeline     | Precision | Recall | F1 Score | Accuracy |
|----------------------|-----------|--------|----------|----------|
| GEN + Disc (BiLSTM)  | 0.28      | 0.59   | 0.38     | 0.74     |
| GEN + Disc (BERT)    | 0.49      | 0.40   | 0.44     | 0.86     |
| GEN + Disc (LogReg*) | 0.68      | 0.65   | 0.67     | 0.91     |

| Generative Stand Alone | Precision | Recall | F1 Score | Accuracy |
|-----------------------|-----------|--------|----------|----------|
| GEN                   | 0.69      | 0.66   | 0.68     | 0.92     |
| GEN + MST-short       | 0.73      | 0.71   | 0.72     | 0.93     |

Table 3: Comparison of local and global models on STAC data.

| Local Model          | Precision | Recall | F1  | Global Model | Precision | Recall | F1  |
|----------------------|-----------|--------|-----|--------------|-----------|--------|-----|
| GEN                  | 0.69      | 0.66   | 0.68| LogReg* on STAC | 0.71      | 0.69   | 0.70|
| LogReg* on STAC      | 0.73      | 0.52   | 0.61|              | 0.65      | 0.64   | 0.65|

et al., 2016) data set. Comparing GEN to LogReg* on our version of the (Perret et al., 2016) data set, GEN has higher scores than LogReg*’s local model; but with a decoding mechanism similar to that reported in (Perret et al., 2016), LogReg*’s global model significantly improves over the GEN’s. We see a 6 point loss in F1 score on GEN’s global model relative to LogReg*’s, even though both used identical MST decoding mechanisms. This is what one would expect from a Snorkel based architecture, although it’s not the rule that we observed for GEN. The only reason GEN did not beat LogReg* is that it did not get a sufficient boost from decoding. We think that this happened because our LFs already contain a lot of global information about the discourse structure, which meant that MST had less of an effect.

Note, however, that even on the (Perret et al., 2016) data set, the MST decoding mechanism provided LogReg* only a boost of 12 F1 points, as seen in Table 4, which is significantly lower than what is reported in (Perret et al., 2016). This 12% boost is the upper limit for boosts with MST that we were able to reproduce. This could be a result of our eliminating the degraded one EDU stories from the data set.

7 Conclusions and Future Work

We have compared a weak supervision approach, inspired by Snorkel, with a standard supervised model on the difficult task of discourse attachment. The results of the model from Snorkel’s generative step surpass those of a standard supervised learning approach, proving it more than competitive with standard approaches. It can also generate a lot of annotated data in a very short time relative to what is needed for a traditional approach: Asher et al. (2016) state that the STAC corpus took at least 4 years to build; we created and refined our labeling functions in two months. In addition, a big advantage of the generative model from the learning point of view is that we don’t have class balancing or drowning problems, which plague problems like discourse attachment. This is because the generative model’s predictions are generated in a very different way from those of a discriminative model, which are based on inductive generalizations. Still it is clear that we must further investigate the interaction of the generative and discriminative models in order to eventually leverage the power of generalization that a discriminative model is supposed to afford.

In future work, we will enrich our weak supervi-
### Table 4: Comparison of Perret 2016 and results of our methods on Perret 2016 data.

| Method            | Local Model |          |          | Global Model |          |          |
|-------------------|-------------|----------|----------|--------------|----------|----------|
|                   | Precision   | Recall   | F1       | Precision    | Recall   | F1       |
| Perret et al. 2016| 0.66        | 0.38     | 0.48     |              |          |          |
| LogReg*           | 0.64        | 0.39     | 0.48     | 0.68         | 0.65     | 0.67     |
| BERT              | 0.43        | 0.31     | 0.36     | 0.46         | 0.47     | 0.46     |
| GEN               | 0.46        | 0.65     | 0.54     | 0.53         | 0.54     | 0.54     |
| GEN + LogReg*     | 0.46        | 0.65     | 0.54     | 0.53         | 0.54     | 0.53     |

### Table 5: F1 scores for different decoding mechanisms with GEN on STAC data.

| Method            | F1 scores of MST variants using GEN inputs |
|-------------------|------------------------------------------|
|                   | MS-DAG | MST | MST/short | MS-DAG/short |
|                   | F1 Score: | 0.70 | 0.70 | 0.72 | 0.72 |

This will lead us to understand how weakly supervised methods can effectively capture the global structural constraints on discourse structures directly without decoding or elaborate learning architectures.

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