Abstract

State-of-the-art image captioners can generate accurate sentences to describe images in a sequence to sequence manner without considering the controllability and interpretability. This, however, is far from making image captioning widely used as an image can be interpreted in infinite ways depending on the target and the context at hand. Achieving controllability is important especially when the image captioner is used by different people with different way of interpreting the images. In this paper, we introduce a novel framework for image captioning which can generate diverse descriptions by capturing the co-dependence between Part-Of-Speech tags and semantics. Our model decouples direct dependence between successive variables. In this way, it allows the decoder to exhaustively search through the latent Part-Of-Speech choices, while keeping decoding speed proportional to the size of the POS vocabulary. Given a control signal in the form of a sequence of Part-Of-Speech tags, we propose a method to generate captions through a Transformer network, which predicts words based on the input Part-Of-Speech tag sequences. Experiments on publicly available datasets show that our model significantly outperforms state-of-the-art methods on generating diverse image captions with high qualities.

1 Introduction

Studies on using image captioning approaches to generate textual descriptions of images has made a great progress recently thanks to the introduction of encoder-decoder architectures (Anderson et al., 2018; Aneja et al., 2018; Karpathy and Fei-Fei, 2017; Lu et al., 2018b; Yang et al., 2020b). The encoder is a Convolutional Neural Network (CNN), first extracting features from the input image. The decoder is a Recurrent Neural Network (RNN) decoding a sentence from the image features, one token at each time. By using this pipeline, a lot of research papers have achieved the state-of-the-art (SOTA) performance on the challenging MS COCO (Lin et al., 2014) and Flickr (Young et al., 2014) dataset, and even outperform human performance on some evaluation metrics. Despite their remarkable performance, many advanced image captioning approaches are not capable to control its predictions, either in the way of changing the length or controlling the patter of generation. However, as we humans can control our way of describing an image, it is desirable for the image captioner to be capable to control how to describe the image either roughly or in details. In this paper, we show that such an ability can be effectively acquired by directly controlling the target side syntax of the captions. We use Part-Of-Speech tag sequences as an extra information and control signal.

Our diverse image captioning method is much based on the approach proposed by Yang et al. (Yang et al., 2019). In that paper, et. al (Yang et al., 2019) proposed a target-side syntax modeling - LaSyn, based deep learning model for the task of controllable neural machine translation. And their model is one of the first two pioneer work in the field of controllable neural machine translation, along with Lakew et al. (Lakew et al., 2019). Our model make an improvement over LaSyn by using Transformer-XL (Dai et al., 2019).

2 Related Work

Image captioning (Yang et al., 2021a, 2020a; Liu et al., 2021) aims to generate short texts that, in natural language, describe an image. Works on generic image captioning, described next, focus on generating captions when the input is only an image. News article image captioning works, described in the section that follows, generate a caption given an image-article pair as input.

In this section, we review related work on generic image captioning and then specifically on news image captioning (Liu et al., 2019; Feng et al.,
2.1 General Image Captioning

Given its many applications, it has attracted an increasing interest in the community. State-of-the-art approaches (Xu et al., 2015; Anderson et al., 2018; Yang et al., 2020b; He et al., 2020) mainly use encoder-decoder frameworks with attention to generate captions for images. Xu et al. (2015) developed soft and hard attention mechanisms to focus on different regions in the image when generating different words. Similarly, Anderson et al. (2018) used a Faster R-CNN (Ren et al., 2015) to extract regions of interest over which an attention mechanism is defined. Yang et al. (2020b) used self-critical sequence training for image captioning. Lu et al. (2018a) and Whitehead et al. (2018) introduced a knowledge aware captioning method where the knowledge comes from metadata associated with the datasets. Rennie et al. (2017) uses CIDEr (Vedantam et al., 2015) score as the reward while Yang et al. (2020b) applies classification score as the training reward. Wang et al. (2020) proposed to use an iterative adaptive refinement method where the knowledge comes from metadata instead of automatic image captioning. Yang et al. (2019) by using images as the input instead of sentences.

In this work, we model syntactic information of target tokens using an additional sequence of variables, which captures the syntactic choices at each time step. There are multiple ways of incorporating this additional information in a sequence-to-sequence model. We follow Yang et al. (2019) of using Part-of-Speech tag sequences as our target side syntax. The model structure is actually a triangle, shown in Figure 1. Our model differs from Yang et al. (2019) using images as the input instead of sentences.

The log-likelihood of the model parameters computed on one training pair $(x, y) \in D$ is given by:

$$
\mathcal{L}(\theta) = \log P(y|x; \theta) = \sum_{n=1}^{N} \log P(y_n|x, y_{<n}; \theta)
$$

Following the mathematical interpretation of Yang et al. (2019), the above equation can be simplified as $Q(z_n) = P(z_n|x, y_{<n}; \theta^{odd})$, the probability of the latent state computed by the decoder. We obtain the lower bound as

$$
\mathcal{L}_{lower}(Q, \theta) = \sum_{n=1}^{N} \sum_{z_n \in V_a} P(z_n|x, y_{<n}; \theta^{odd}) \times \log P(y_n, z_n|x, y_{<n}; \theta)
$$

where, $\theta$ denotes the parameters of both the encoder and the decoder.

Figure 1: Our proposed method is actually a triangle structure.

In this work, we model syntactic information of target tokens using an additional sequence of variables, which captures the syntactic choices at each time step. There are multiple ways of incorporating this additional information in a sequence-to-sequence model. We follow Yang et al. (2019) of using Part-of-Speech tag sequences as our target side syntax. The model structure is actually a triangle, shown in Figure 1. Our model differs from Yang et al. (2019) by using images as the input instead of sentences.

The log-likelihood of the model parameters computed on one training pair $(x, y) \in D$ is given by:

$$
\mathcal{L}(\theta) = \log P(y|x; \theta)
$$

$$
= \sum_{n=1}^{N} \log P(y_n|x, y_{<n}; \theta)
$$

$$
= \sum_{n=1}^{N} \log \sum_{z_n \in V_a} P(y_n, z_n|x, y_{<n})
$$

Following the mathematical interpretation of Yang et al. (2019), the above equation can be simplified as $Q(z_n) = P(z_n|x, y_{<n}; \theta^{odd})$, the probability of the latent state computed by the decoder. We obtain the lower bound as

$$
\mathcal{L}_{lower}(Q, \theta) = \sum_{n=1}^{N} \sum_{z_n \in V_a} P(z_n|x, y_{<n}; \theta^{odd}) \times \log P(y_n, z_n|x, y_{<n}; \theta)
$$

where, $\theta$ denotes the parameters of both the encoder and the decoder.

In this work, we model syntactic information of target tokens using an additional sequence of variables, which captures the syntactic choices at each time step. There are multiple ways of incorporating this additional information in a sequence-to-sequence model. We follow Yang et al. (2019) of using Part-of-Speech tag sequences as our target side syntax. The model structure is actually a triangle, shown in Figure 1. Our model differs from Yang et al. (2019) by using images as the input instead of sentences.

The log-likelihood of the model parameters computed on one training pair $(x, y) \in D$ is given by:

$$
\mathcal{L}(\theta) = \log P(y|x; \theta)
$$

$$
= \sum_{n=1}^{N} \log P(y_n|x, y_{<n}; \theta)
$$

$$
= \sum_{n=1}^{N} \log \sum_{z_n \in V_a} P(y_n, z_n|x, y_{<n})
$$

Following the mathematical interpretation of Yang et al. (2019), the above equation can be simplified as $Q(z_n) = P(z_n|x, y_{<n}; \theta^{odd})$, the probability of the latent state computed by the decoder. We obtain the lower bound as

$$
\mathcal{L}_{lower}(Q, \theta) = \sum_{n=1}^{N} \sum_{z_n \in V_a} P(z_n|x, y_{<n}; \theta^{odd}) \times \log P(y_n, z_n|x, y_{<n}; \theta)
$$

where, $\theta$ denotes the parameters of both the encoder and the decoder.

In this work, we model syntactic information of target tokens using an additional sequence of variables, which captures the syntactic choices at each time step. There are multiple ways of incorporating this additional information in a sequence-to-sequence model. We follow Yang et al. (2019) of using Part-of-Speech tag sequences as our target side syntax. The model structure is actually a triangle, shown in Figure 1. Our model differs from Yang et al. (2019) by using images as the input instead of sentences.

The log-likelihood of the model parameters computed on one training pair $(x, y) \in D$ is given by:

$$
\mathcal{L}(\theta) = \log P(y|x; \theta)
$$

$$
= \sum_{n=1}^{N} \log P(y_n|x, y_{<n}; \theta)
$$

$$
= \sum_{n=1}^{N} \log \sum_{z_n \in V_a} P(y_n, z_n|x, y_{<n})
$$

Following the mathematical interpretation of Yang et al. (2019), the above equation can be simplified as $Q(z_n) = P(z_n|x, y_{<n}; \theta^{odd})$, the probability of the latent state computed by the decoder. We obtain the lower bound as

$$
\mathcal{L}_{lower}(Q, \theta) = \sum_{n=1}^{N} \sum_{z_n \in V_a} P(z_n|x, y_{<n}; \theta^{odd}) \times \log P(y_n, z_n|x, y_{<n}; \theta)
$$

where, $\theta$ denotes the parameters of both the encoder and the decoder.

In this work, we model syntactic information of target tokens using an additional sequence of variables, which captures the syntactic choices at each time step. There are multiple ways of incorporating this additional information in a sequence-to-sequence model. We follow Yang et al. (2019) of using Part-of-Speech tag sequences as our target side syntax. The model structure is actually a triangle, shown in Figure 1. Our model differs from Yang et al. (2019) by using images as the input instead of sentences.

The log-likelihood of the model parameters computed on one training pair $(x, y) \in D$ is given by:

$$
\mathcal{L}(\theta) = \log P(y|x; \theta)
$$

$$
= \sum_{n=1}^{N} \log P(y_n|x, y_{<n}; \theta)
$$

$$
= \sum_{n=1}^{N} \log \sum_{z_n \in V_a} P(y_n, z_n|x, y_{<n})
$$

Following the mathematical interpretation of Yang et al. (2019), the above equation can be simplified as $Q(z_n) = P(z_n|x, y_{<n}; \theta^{odd})$, the probability of the latent state computed by the decoder. We obtain the lower bound as

$$
\mathcal{L}_{lower}(Q, \theta) = \sum_{n=1}^{N} \sum_{z_n \in V_a} P(z_n|x, y_{<n}; \theta^{odd}) \times \log P(y_n, z_n|x, y_{<n}; \theta)
$$

where, $\theta$ denotes the parameters of both the encoder and the decoder.

In this work, we model syntactic information of target tokens using an additional sequence of variables, which captures the syntactic choices at each time step. There are multiple ways of incorporating this additional information in a sequence-to-sequence model. We follow Yang et al. (2019) of using Part-of-Speech tag sequences as our target side syntax. The model structure is actually a triangle, shown in Figure 1. Our model differs from Yang et al. (2019) by using images as the input instead of sentences.
where

\[
Q(\theta, \theta^{old}) = \sum_{n=1}^{N} \sum_{z_n \in V_n} P(z_n|\mathbf{x}, \mathbf{y}_{\leq n}; \theta^{old}) \times \log P(\mathbf{y}_n, z_n|\mathbf{x}, \mathbf{y}_{<n}; \theta)
\]

EM algorithm for optimizing \( Q(\theta, \theta^{old}) \) consists of two major steps. In the E-step, we compute the posterior distribution of \( z_n \) with respect to \( \theta^{old} \) by

\[
\gamma(z_n = i) = \frac{P(z_n = i|x, y_{\leq n})}{\sum_{i=1}^{N} P(y_n, z_n = i|x, y_{<n})}
\]

where \( \gamma(z_n = i) \) is the responsibility of \( z_n = i \) given \( y_n \).

In the M-step, the goal is to find the configuration of \( \theta \) that would maximize the expected log-likelihood using the posteriors computed in the E-step. In conventional EM algorithm for shallow probabilistic graphical model, the M-step is generally supposed to have closed-form solution. However, we model the probabilistic dependencies by deep neural networks, where \( Q(\theta, \theta^{old}) \) is highly non-convex and non-linear with respect to network parameters \( \theta \). Therefore, there exists no analytical solution to maximize it. However, since deep neural network is differentiable, we can update \( \theta \) by taking a gradient ascent step:

\[
\theta^{new} = \theta^{old} + \eta \frac{\partial Q(\theta, \theta^{old})}{\partial \theta}
\]

The resulting algorithm belongs to the class of generalized EM algorithms and is guaranteed (for a sufficiently small learning rate \( \eta \)) to converge to a (local) optimum of the data log likelihood.

## 4 Evaluation

We evaluate our proposed model on COCO image captioning dataset. We describe the datasets in more details in the appendix. COCO. The dataset is the most popular benchmark for image captioning, which contains 82,783 training images and 40,504 validation images. There are 5 human annotated descriptions per image. As the annotations of the official test set are not publicly available, we follow the widely used splits provided by (Karpathy and Fei-Fei, 2017), where 5,000 images are used for validation, 5,000 for testing and the rest for training. We convert all the descriptions in the training set to lower case and discard rare words which occur less than 5 times, resulting in the final vocabulary with 10,201 unique words in the COCO dataset.

### 4.1 Methods & Metrics

We compare against three types of baselines. (i) The CNN-LSTM (Hochreiter and Schmidhuber, 1997) based models: Up-Down (Anderson et al., 2018) which uses attention over regions of interest, NBT (Lu et al., 2018b) that first generates a sentence ‘template’ and then fill in by visual concepts identified by object detectors, Att2all (Rennie et al., 2017) that uses self-critical sequence training for image captioning, and AoA (Huang et al., 2019) which uses attention on attention for encoding image regions and an LSTM language model: (ii) Transformer-based models: \( \mathcal{M}^2 \)-T (Cornia et al., 2020) which uses a mesh-like connectivity to learn prior knowledge, Image-T (He et al., 2020), an image transformer, Object-T (Herdade et al., 2019) that models the spatial relationship between objects, and ETA (Li et al., 2019) which proposes the entangled attention mechanism; (iii) The GCN-LSTM based models: VSUA (Longteng et al., 2019) that uses GCNs to model the semantic and geometric interactions of the objects, GCN (Yao et al., 2018) which exploits pairwise relationships between image regions through a GCN, and SGAE (Yang et al., 2019) which instead uses auto-encoding scene graphs.

For the caption generation evaluation, we follow the other baselines and use the BLEU-1 and BLEU-4 (Papineni et al., 2002), ROUGE (Lin, 2004), METEOR (Denkowski and Lavie, 2014), CIDEr (Vedantam et al., 2015) and SPICE (Anderson et al., 2016) metrics.

For all image captioning tasks, we choose the base configuration of Transformer with \( d_{\text{model}} = 512 \). During training, we choose Adam optimizer (Kingma and Ba, 2015) with \( \beta_1 = 0.9 \), \( \beta_2 = 0.98 \) with initial learning rate is 0.0002 with 4000 warm-up steps. We describe additional implementation and training details in the Appendix. We implement all Transformer-based models using Fairseq\(^2\) Pytorch framework.

For all captioning tasks, we choose the base configuration of Transformer with \( d_{\text{model}} = 512 \). During training, we choose Adam optimizer (Kingma

\(^2\)https://github.com/pytorch/fairseq
and Ba, 2015) with $\beta_1 = 0.9$, $\beta_2 = 0.98$. The initial learning rate is 0.0001 with 4000 warm-up steps. The learning rate is scheduled with the same rule as in (Vaswani et al., 2017). For inference, we use beam search with beam size 5 to generate candidates.

4.2 Results on COCO

Table 1 compares our model against some of the state-of-the-art models on the COCO dataset. It is normal that our model cannot achieve best results compared with other models because the main goal of it not to get best automatic caption evaluation score, but to get the most diverse generate captions.

4.3 Diversity

We compare the diversity of generated captions using distinct-1 score, which is simply the number of distinct unigrams divided by total number of generated words. We use our model to generate 10 translations for each source sentence of the test dataset. We then compare our results with baseline Transformer. The result is shown in Table 2. The results showed that our model can generate more diverse captions.

5 Conclusion

In this work, we presented a novel controllable image captioning model, that latent part-of-speech syntax can be decently incorporated at the target side. On the common COCO captioning tasks, we achieve competitive results. Our future work includes extending our model to integrate other more useful and complicated features, like dependency tree or other syntax which might output better results.

References

Peter Anderson, Basura Fernando, Mark Johnson, and Stephen Gould. 2016. Spice: Semantic propositional image caption evaluation. In ECCV.

Peter Anderson, Xiaodong He, Chris Buehler, Damien Teney, Mark Johnson, Stephen Gould, and Lei Zhang. 2018. Bottom-up and top-down attention for image captioning and visual question answering. In The IEEE Conference on Computer Vision and Pattern Recognition (CVPR).

J. Aneja, A. Deshpande, and A. G. Schwing. 2018. Convolutional image captioning. In 2018 IEEE Conference on Computer Vision and Pattern Recognition.

Marcella Cornia, Matteo Stefanini, Lorenzo Baraldi, and Rita Cucchiara. 2020. Meshed-Memory Transformer for Image Captioning. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition.

Zihang Dai, Zhilin Yang, Yiming Yang, Jaime Carbonell, Quoc Le, and Ruslan Salakhutdinov. 2019. Transformer-XL: Attentive language models beyond a fixed-length context. In Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics, pages 2978–2988, Florence, Italy. Association for Computational Linguistics.

Michael Denkowski and Alon Lavie. 2014. Meteor universal: Language specific translation evaluation for any target language. In Proceedings of the Ninth Workshop on Statistical Machine Translation.

Z. Feng, Q. Zhou, J. Zhang, P. Jiang, and X. Yang. 2015. A target guided subband filter for acoustic event detection in noisy environments using wavelet packets. IEEE/ACM Transactions on Audio, Speech, and Language Processing, 23:361–372.

Sen He, Wentong Liao, Hamed Rezazadegan Tavakoli, Michael Ying Yang, Bodo Rosenhahn, and Nicolas Puegault. 2020. Image captioning through image transformer. In Proceedings of the European Conference on Computer Vision (ECCV).

Simao Herdade, Armin Kappeler, Kofi Boakye, and Joao Soares. 2019. Image captioning: Transforming objects into words. In Advances in Neural Information Processing Systems 32.

Sepp Hochreiter and Jürgen Schmidhuber. 1997. Long short-term memory. Neural computation.

Lun Huang, Wennin Wang, Jie Chen, and Xiao-Yong Wei. 2019. Attention on attention for image captioning. In International Conference on Computer Vision.

Andrei Karpathy and Li Fei-Fei. 2017. Deep visual-semantic alignments for generating image descriptions. IEEE Trans. Pattern Anal. Mach. Intell.

Diederik P. Kingma and Jimmy Ba. 2015. Adam: A method for stochastic optimization. In ICLR.

Surafel Melaku Lakew, Mattia Di Gangi, and Marcello Federico. 2019. Controlling the output length of neural machine translation. In Proceedings of the 16th International Conference on Spoken Language Translation, Hong Kong.

Guang Li, Linchao Zhu, Ping Liu, and Yi Yang. 2019. Entangled transformer for image captioning. In Proceedings of the IEEE/CVF International Conference on Computer Vision (ICCV).

Chin-Yew Lin. 2004. ROUGE: A package for automatic evaluation of summaries. In Text Summarization Branches Out.
Table 1: Results on COCO dataset. We only report the single model results on the ‘Karpathy’ test split. We highlight the our model in bold.

| Method                     | B-1 | B-4 | M   | R   | C   | S   |
|---------------------------|-----|-----|-----|-----|-----|-----|
| Up-Down (Anderson et al., 2018) | 79.8| 36.3| 27.7| 56.9| 120.1| 21.4|
| NBT (Lu et al., 2018b)    | 75.5| 34.7| 27.1| 54.7| 107.2| 20.1|
| AoA (Huang et al., 2019)  | 80.2| 39.9| 28.8| 55.9| 126.6| 22.7|
| Image-T (He et al., 2020) | 80.8| 39.5| 29.1| 59.0| 130.8| 22.8|
| \( M^2 \)-T (Cornia et al., 2020) | 80.8| 39.1| 29.2| 58.6| 131.2| 22.6|
| GCN (Yao et al., 2018)    | 80.5| 38.2| 28.5| 58.3| 127.6| 22.0|
| SGAE (Yang et al., 2019)  | 80.8| 38.4| 28.4| 58.6| 127.8| 22.1|
| Reformer (Yang et al., 2021b) | 82.3| 39.8| 29.7| 59.8| 131.9| 23.0|
| Ours                      | 72.3| 32.8| 25.7| 54.8| 108.9| 20.0|

Table 2: Diversity generation evaluation. We highlight the best model in bold.

| Model                  | distinct-1 |
|------------------------|------------|
| GCN (Yao et al., 2018) | 0.231      |
| Image-T (He et al., 2020) | 0.232     |
| Reformer (Yang et al., 2021b) | 0.228     |
| \( M^2 \)-T (Cornia et al., 2020) | 0.237     |

Shaoqing Ren, Kaiming He, Ross Girshick, and Jian Sun. 2015. Faster r-cnn: Towards real-time object detection with region proposal networks. In Advances in Neural Information Processing Systems 28.

Steven J. Rennie, Etienne Marcheret, Youssef Mrouech, Jerret Ross, and Vaibhava Goel. 2017. Self-critical sequence training for image captioning. IEEE Conference on Computer Vision and Pattern Recognition (CVPR).

Fawaz Samman and Luke Melas-Kyriazi. 2020. Show, edit and tell: A framework for editing image captions. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR).

Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, \( \text{Ł} \) ukasz Kaiser, and Illia Polosukhin. 2017. Attention is all you need. In Advances in Neural Information Processing Systems 30.

Ramakrishna Vedantam, C. Lawrence Zitnick, and Devi Parikh. 2015. Cider: Consensus-based image description evaluation. In CVPR.

Zeyu Wang, Berthy Feng, Karthik Narasimhan, and Olga Russakovsky. 2020. Towards unique and informative captioning of images. In Proceedings of the European Conference on Computer Vision (ECCV).

Spencer Whitehead, Heng Ji, Mohit Bansal, Shih-Fu Chang, and Clare Voss. 2018. Incorporating background knowledge into video description generation. In Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing.

Kelvin Xu, Jimmy Ba, Ryan Kiros, Kyunghyun Cho, Aaron Courville, Ruslan Salakhudinov, Rich Zemel, and Yoshua Bengio. 2015. Show, attend and tell: Neural image caption generation with visual attention. In Proceedings of the 32nd International Conference on Machine Learning.

X. Yang, K. Tang, H. Zhang, and J. Cai. 2019. Auto-encoding scene graphs for image captioning. In
Xuewen Yang, Svebor Karaman, Joel Tetreault, and Alejandro Jaimes. 2021a. Journalistic guidelines aware news image captioning. In Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing, pages 5162–5175, Online and Punta Cana, Dominican Republic. Association for Computational Linguistics.

Xuewen Yang, Yingru Liu, and Xin Wang. 2021b. Reformer: The relational transformer for image captioning. CoRR, abs/2107.14178.

Xuewen Yang, Yingru Liu, Dongliang Xie, Xin Wang, and Niranjan Balasubramanian. 2019. Latent part-of-speech sequences for neural machine translation. In Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP), pages 780–790, Hong Kong, China. Association for Computational Linguistics.

Xuewen Yang, Dongliang Xie, and Xin Wang. 2020a. Crossing-domain generative adversarial networks for unsupervised multi-domain image-to-image translation. CoRR, abs/2008.11882.

Xuewen Yang, Heming Zhang, Di Jin, Yingru Liu, Chihao Wu, Jianchao Tan, Dongliang Xie, Jue Wang, and Xin Wang. 2020b. Fashion captioning: Towards generating accurate descriptions with semantic rewards. In Proceedings of the European Conference on Computer Vision (ECCV).

Ting Yao, Yingwei Pan, Yehao Li, and Tao Mei. 2018. Exploring visual relationship for image captioning. In Proceedings of the European Conference on Computer Vision (ECCV).

Peter Young, Alice Lai, Micah Hodosh, and Julia Hockenmaier. 2014. From image descriptions to visual denotations: New similarity metrics for semantic inference over event descriptions. TACL, 2:67–78.