CharManteau: Character Embedding Models For Portmanteau Creation

Varun Gangal; Harsh Jhamtani; Graham Neubig, Eduard Hovy, Eric Nyberg
Language Technologies Institute,
Carnegie Mellon University
{vgangal, jharsh, gneubig, hovy, ehn}@cs.cmu.edu

Abstract

Portmanteaus are a word formation phenomenon where two words are combined to form a new word. We propose character-level neural sequence-to-sequence (S2S) methods for the task of portmanteau generation that are end-to-end-trainable, language independent, and do not explicitly use additional phonetic information. We propose a noisy-channel-style model, which allows for the incorporation of unsupervised word lists, improving performance over a standard source-to-target model. This model is made possible by an exhaustive candidate generation strategy specifically enabled by the features of the portmanteau task. Experiments find our approach superior to a state-of-the-art FST-based baseline with respect to ground truth accuracy and human evaluation.

1 Introduction

Portmanteaus (or lexical blends Algeo (1977)) are novel words formed from parts of multiple root words in order to refer to a new concept which can’t otherwise be expressed concisely. Portmanteaus have become frequent in modern-day social media, news reports and advertising, one popular example being Brexit (Britain + Exit). Petri (2012). These are found not only in English but many other languages such as Bahasa Indonesia Dardjowidjojo (1979), Modern Hebrew Bat-El (1996); Berman (1989) and Spanish Piñeros (2004). Their short length makes them ideal for headlines and brandnames (Gabler, 2015). Unlike better-defined morphological phenomenon such as inflection and derivation, portmanteau generation is difficult to capture using a set of rules. For instance, Shaw et al. (2014) state that the composition of the portmanteau from its root words depends on several factors, two important ones being maintaining prosody and retaining character segments from the root words, especially the head. An existing work by Deri and Knight (2015) aims to solve the problem of predicting portmanteau using a multi-tape FST model, which is data-driven, unlike prior approaches. Their methods rely on a grapheme to phoneme converter, which takes into account the phonetic features of the language, but may not be available or accurate for non-dictionary words, or low resource languages.

Prior works, such as Faruqui et al. (2016), have demonstrated the efficacy of neural approaches for morphological tasks such as inflection. We hypothesize that such neural methods can (1) provide a simpler and more integrated end-to-end framework than multiple FSTs used in the previous work, and (2) automatically capture features such as phonetic similarity through the use of char-
acter embeddings, removing the need for explicit grapheme-to-phoneme prediction. To test these hypotheses, in this paper, we propose a neural S2S model to predict portmanteaus given the two root words, specifically making 3 major contributions:

- We propose an S2S model that attends to the two input words to generate portmanteaus, and an additional improvement that leverages noisy-channel-style modelling to incorporate a language model over the vocabulary of words (§2).
- Instead of using the model to directly predict output character-by-character, we use the features of portmanteaus to exhaustively generate candidates, making scoring using the noisy channel model possible (§3).
- We curate and share a new and larger dataset of 1624 portmanteaus (§4).

In experiments (§5), our model performs better than the baseline Deri and Knight (2015) on both objective and subjective measures, demonstrating that such methods can be used effectively in a morphological task.

2 Proposed Models

This section describes our neural models.

2.1 Forward Architecture

Under our first proposed architecture, the input sequence $x = \text{concat}(x^{(1)}, \ldots, x^{(2)})$, while the output sequence is the portmanteau $y$. The model learns the distribution $P(y|x)$. The network architecture we use is an attentional S2S model (Bahdanau et al., 2014). We use a bidirectional encoder, which is known to work well for S2S problems with similar token order, which is true in our case. Let $\text{LSTM}$ and $\overline{\text{LSTM}}$ represent the forward and reverse encoder; $e_{\text{enc}}()$ and $e_{\text{dec}}()$ represent the character embedding functions used by encoder and decoder.

The following equations describe the model:

$$
\begin{align*}
    h^{\text{enc}}_0 &= \overline{0}, h^{\text{enc}}_{|x|} = \overline{0} \\
    h^{\text{enc}}_t &= \overline{\text{LSTM}}(h^{\text{enc}}_{t-1}, e_{\text{enc}}(x_t)) \\
    h^{\text{enc}}_t &= \overline{\text{LSTM}}(h^{\text{enc}}_{t-1}, e_{\text{enc}}(x_t)) \\
    h^{\text{dec}}_t &= h^{\text{enc}}_t + h^{\text{enc}}_t \\
    h^{\text{dec}}_0 &= \overline{\text{LSTM}}(h^{\text{dec}}_{|x|}, \text{concat}(e_{\text{dec}}(y_{t-1}), c_{t-1})) \\
    p_t &= \text{softmax}(W_{\text{h}s}[\text{concat}(h^{\text{dec}}_t, c_t)] + b_s)
\end{align*}
$$

The context vector $c_t$ is computed using dot-product attention over encoder states. We choose dot-product attention because it doesn’t add extra parameters, which is important in a low-data scenario such as portmanteau generation.

$$
\begin{align*}
    a_t^i &= \text{dot}(h^{\text{enc}}_t, h^{\text{enc}}_i), a_t^j &= \text{softmax}(a_t^i) \\
    c_t &= \sum_{i=1}^{n} a_t^i h^{\text{enc}}_i
\end{align*}
$$

In addition to capturing the fact that portmanteaus of two English words typically sound English-like, and to compensate for the fact that available portmanteau data will be small, we pre-train the character embeddings on English language words. We use character embeddings learnt using an LSTM language model over words in an English dictionary, where each word is a sequence of characters, and the model will predict next character in sequence conditioned on previous characters in the sequence.

2.2 Backward Architecture

The second proposed model uses Bayes’s rule to reverse the probabilities $P(y|x) = \frac{P(x|y)P(y)}{P(x)}$ to get $\text{argmax}_y P(y|x) = \text{argmax}_y P(x|y)P(y)$. Thus, we have a reverse model of the probability $P(x|y)$ that the given root words were generated from the portmanteau and a character language model model $P(y)$. This is a probability distribution over all character sequences $y \in A^*$, where $A$ is the alphabet of the language. This way of factorizing the probability is also known as a noisy channel model, which has recently also been shown to be effective for neural MT (Hoang et al. (2017), Yu et al. (2016)). Such a model offers two advantages

1. The reverse direction model (or alignment model) gives higher probability to those portmanteaus from which one can discern the root words easily, which is one feature of good portmanteaus.
2. The character language model $P(y)$ can be trained on a large vocabulary of words in the language. The likelihood of a word $y$ is factorized as $P(y) = \prod_{i=1}^{\text{|y|}} P(y_i|y_{i-1})$, where $y_i = y_i, y_{i+1} \ldots y_j$, and we train an LSTM to maximize this likelihood.

1 Specifically in our experiments, 134K words from the CMU dictionary (Weide, 1998).
3 Making Predictions

Given these models, we must make predictions, which we do by two methods.

**Greedy Decoding:** In most neural sequence-to-sequence models, we perform autoregressive greedy decoding, selecting the next character greedily based on the probability distribution for the next character at current time step. We refer to this decoding strategy as **Greedy**.

**Exhaustive Generation:** Many portmanteaus were observed to be concatenation of a prefix of the first word and a suffix of the second. We therefore generate all candidate outputs which follow this rule. Thereafter we score these candidates with the decoder and output the one with the maximum score. We refer to this decoding strategy as **Score**.

Given that our training data is small in size, we expect ensembling (Breiman, 1996) to help reduce model variance and improve performance. In this paper, we ensemble our models wherever mentioned by training multiple models on 80% subsamples of the training data, and averaging log probability scores across the ensemble at test-time.

4 Dataset

The existing dataset by Deri and Knight (2015) contains 401 portmanteau examples from Wikipedia. We refer to this dataset as **Wiki**. Besides being small for detailed evaluation, **Wiki** is biased by being from just one source. We manually collect **Large**, a dataset of 1624 distinct English portmanteaus from following sources:

- Urban Dictionary
- Wikipedia
- Wiktionary
- BCU’s Neologism Lists from ’94 to ’12.

Naturally, **Wiki** ⊂ **Large**. We define **Blind** = **Large** - **Wiki** as the dataset of 1223 examples not from Wikipedia. We observed that 84.7% of the words in **Large** can be generated by concatenating prefix of first word with a suffix of the second.

---

Table 1: 10-Fold Cross-Validation results, **Wiki**, **Attn**, **Ens**, **Init** denote attention, ensembling, and initializing character embeddings respectively.

| Model | Attn | Ens | Init | Prediction | Matches | Distance |
|-------|------|-----|------|------------|---------|----------|
| BASELINE | ✓ | ✗ | ☑ | GREEDY | 35.9% | 1.59 |
| FORWARD | ✓ | ✗ | ☑ | GREEDY | 22.0% | 1.98 |
| ✓ | ✗ | ☑ | BEAM | 28.0% | 1.90 | 1.13 |
| ✓ | ✗ | ☑ | BEAM | 13.25% | 2.47 | 2.37 |
| ✓ | ✗ | ☑ | BEAM | 15.25% | 2.37 | 1.64 |
| ✓ | ✗ | ☑ | SCORE | 30.25% | 1.64 | 1.33 |
| ✓ | ✗ | ☑ | SCORE | 32.88% | 1.53 | 1.34 |
| ✓ | ✗ | ☑ | SCORE | 42.25% | 1.33 | 3.76 |
| ✓ | ✗ | ☑ | SCORE | 41.25% | 1.34 | 3.76 |
| ✓ | ✗ | ☑ | SCORE | 6.75% | 3.76 | 3.95 |
| ✓ | ✗ | ☑ | SCORE | 6.50% | 3.76 | 3.95 |
| ✓ | ✗ | ☑ | SCORE | 5.00% | 3.95 | 3.95 |
| ✓ | ✗ | ☑ | SCORE | 4.75% | 3.98 | 3.98 |

Table 1: 10-Fold Cross-Validation results, **Wiki**.

5 Experiments

In this section, we show results comparing various configurations of our model to the baseline FST model of Deri and Knight (2015) (BASELINE). Models are evaluated using exact-matches (Matches) and average Levenshtein edit-distance (Distance) w.r.t ground truth.

5.1 Objective Evaluation Results

In Experiment 1, we follow the same setup as Deri and Knight (2015). **Wiki** is split into 10 folds. Each fold model uses 8 folds for training, 1 for validation, and 1 for test. The average (10 fold cross-validation style approach) performance metrics on the test fold are then evaluated. Table 1 shows the results of Experiment 1 for various model configurations. We get the BASELINE numbers from Deri and Knight (2015). Our best model obtains 48.75% *Matches* and 1.12 *Distance*, compared to 45.39% *Matches* and 1.59 *Distance* using BASELINE.

For Experiment 2, we seek to compare our best approaches from Experiment 1 to the BASELINE on a large, held-out dataset. Each model is trained on **Wiki** and tested on **Blind**. BASELINE was similarly trained only on **Wiki**, making it a fair comparison. Table 2 shows the results. Our best model gets *Distance* of 1.96 as compared to 2.32 from BASELINE.

We observe that the **Backward** architecture performs better than **Forward** architecture, confirming our hypothesis in §2.2. In addition, ablation...
Table 2: Results on $D_{\text{Blind}}$ (1223 Examples). In general, BACKWARD architecture performs better than FORWARD architecture.

![Attention matrices while generating slurve from slider;curve, and bennifer from ben;jennifer respectively, using Forward model. ; and , are separator and stop characters. Darker cells are higher-valued](image)

![Figure 2: Attention matrices while generating slurve from slider;curve, and bennifer from ben;jennifer respectively, using Forward model. ; and , are separator and stop characters. Darker cells are higher-valued](image)

5.3 Subjective Evaluation and Analysis

On inspecting outputs, we observed that often output from our system seemed good in spite of high edit distance from ground truth. Such aspect of an output seeming good is not captured satisfactorily by measures like edit distance. To compare the errors made by our model to the baseline, we designed and conducted a human evaluation task on AMT. In the survey, we show human annotators outputs from our system and that of the baseline. We asked them to judge which alternative is better overall based on following criteria: 1. It is a good shorthand for two original words 2. It sounds better. We requested annotation on a scale of 1-4. To avoid ordering bias, we shuffled the order of two portmanteau between our system and that of baseline. We restrict annotators to be from Anglophone countries, have HIT Approval Rate > 80% and pay 0.40$ per HIT (5 Questions per HIT).

As seen in Table 4, output from our system was labelled better by humans as compared to the baseline 58.12% of the time. Table 3 shows outputs from different models for a few examples.

Table 3: Example outputs from different models (Refer to appendix for more examples)

| Model          | Attr | Ens | Init | Search | Matches | Distance |
|----------------|------|-----|------|--------|---------|----------|
| BASELINE       | ✓    |     |      |        | 31.56%  | 2.35     |
| FORWARD        | ✓    | ×   | ✓    |        | 25.26%  | 2.13     |
|                | ✓    | ×   |      |        | 24.93%  | 2.32     |
|                | ✓    | ×   |      |        | 31.23%  | 1.98     |
|                | ✓    | ✓   | ✓    |        | 31.72%  | 1.96     |
|                | ✓    | ✓   |      |        | 32.78%  | 1.96     |
| BACKWARD       | ✓    | ×   | ✓    |        | 25.75%  | 2.14     |
|                | ✓    | ×   |      |        | 25.36%  | 2.17     |
|                | ✓    | ✓   |      |        | 31.72%  | 1.96     |
|                | ✓    | ✓   |      |        | 32.78%  | 1.96     |

BACKWARD is indeed statistically significantly better than BASELINE in terms of Matches.

In order to do this, we use a paired bootstrap comparison (Koehn, 2004) between BACKWARD and BASELINE in terms of Matches. BACKWARD is found to be better (gets more Matches) than BASELINE in 99.9% ($p = 0.999$) of the subsets.

Similarly, BACKWARD has a lower Distance than BASELINE by a margin of 0.2 in 99.5% ($p = 0.995$) of the subsets.

6 Related Work

Özbal and Strapparava (2012) generate new words to describe a product given its category and properties. However, their method is limited to handcrafted rules as compared to our data driven ap-

---

4 We average across $M = 1000$ randomly chosen subsets of $D_{\text{Blind}}$, each of size $N = 631$ (≈ 1223/2).

5 We avoid ground truth comparison because annotators can be biased to ground truth due to its existing popularity.
Table 4: AMT annotator judgements on whether our system’s proposed portmanteau is better or worse compared to the baseline

| Judgement     | Percentage of total |
|---------------|---------------------|
| Much Better (1)| 29.06               |
| Better (2)     | 29.06               |
| Worse (3)      | 25.11               |
| Much Worse (4)| 16.74               |

proach. Also, their focus is on brand names. Hiranandani et al. (2017) have proposed an approach to recommend brand names based on brand/product description. However, they consider only a limited number of features like memorability and readability. Smith et al. (2014) devise an approach to generate portmanteaus, which requires user-defined weights for attributes like sounding good. Generating a portmanteau from two root words can be viewed as a S2S problem. Recently, neural approaches have been used for S2S problems (Sutskever et al., 2014) such as MT. Ling et al. (2015) and Chung et al. (2016) have shown that character-level neural sequence models work as well as word-level ones for language modelling and MT. Zoph and Knight (2016) propose S2S models for multi-source MT, which have multi-sequence inputs, similar to our case.

7 Conclusion

We have proposed an end-to-end neural system to model portmanteau generation. Our experiments show the efficacy of proposed system in predicting portmanteaus given the root words. We conclude that pre-training character embeddings on the English vocabulary helps the model. Through human evaluation we show that our model’s predictions are superior to the baseline. We have also released our dataset and code6 to encourage further research on the phenomenon of portmanteaus. We also release an online demo7 where our trained model can be queried for portmanteau suggestions. An obvious extension to our work is to try similar models on multiple languages.

Acknowledgements

We thank Dongyeop Kang, David Mortensen, Qinlan Shen and anonymous reviewers for their valuable comments. This research was supported in part by DARPA grant FA8750-12-0342 funded under the DEFT program.

References

John Algeo. 1977. Blends, a structural and systemic view. American speech 52(1/2):47–64.
Dzmitry Bahdanau, Kyunghyun Cho, and Yoshua Bengio. 2014. Neural machine translation by jointly learning to align and translate. arXiv:1409.0473.
Outi Bat-El. 1996. Selecting the best of the worst: the grammar of Hebrew blends. Phonology 13(03):283–328.
Ruth Berman. 1989. The role of blends in Modern Hebrew word-formation. Studio linguistica et orientalia memoriae Haim Blanc dedicata. Wiesbaden: Harrassowitz pages 45–61.
Leo Breiman. 1996. Bagging predictors. Machine learning 24(2):123–140.
Junyoung Chung, Kyunghyun Cho, and Yoshua Bengio. 2016. A character-level decoder without explicit segmentation for neural machine translation. arXiv:1603.06147.
Soenjono Dardjowidjojo. 1979. Acronymic Patterns in Indonesian. Pacific Linguistics Series C 45:143–160.
Aliya Deri and Kevin Knight. 2015. How to make a frenemy: Multitape FSTs for portmanteau generation. In Proceedings of NAACL-HLT. pages 206–210.
Manaal Faruqui, Yulia Tsvetkov, Graham Neubig, and Chris Dyer. 2016. Morphological Inflection Generation using Character Sequence to Sequence Learning. In Proceedings of NAACL-HLT. pages 634–643.
Neal Gabler. 2015. The Weird Science of Naming New Products. New York Times - http://tinyurl.com/1mlq7ex.
Gaurush Hiranandani, Pranav Maneriker, and Harsh Jhamtani. 2017. Generating appealing brand names. arXiv preprint arXiv:1706.09335.
Cong Duy Vu Hoang, Gholamreza Haffari, and Trevor Cohn. 2017. Decoding as Continuous Optimization in Neural Machine Translation. arXiv:1701.02854.
Philipp Koehn. 2004. Statistical significance tests for machine translation evaluation. In EMNLP. pages 388–395.
Wang Ling, Isabel Trancoso, Chris Dyer, and Alan W Black. 2015. Character-based neural machine translation. arXiv:1511.04586.
Gözde Özbal and Carlo Strapparava. 2012. A computational approach to the automation of creative naming. In Proceedings of ACL. Association for Computational Linguistics, pages 703–711.

Alexandra Petri. 2012. Say No to Portmanteaus. Washington Post - http://tinyurl.com/kvmep2t.

Carlos-Eduardo Piñeros. 2004. The creation of portmanteaus in the extragrammatical morphology of Spanish. Probus 16(2):203–240.

Katherine E Shaw, Andrew M White, Elliott Moreton, and Fabian Monrose. 2014. Emergent faithfulness to morphological and semantic heads in lexical blends. In Proceedings of the Annual Meetings on Phonology. volume 1.

Michael R Smith, Ryan S Hintze, and Dan Ventura. 2014. Nehovah: A neologism creator nomen ipsum. In Proceedings of the International Conference on Computational Creativity. pages 173–181.

Ilya Sutskever, Oriol Vinyals, and Quoc V Le. 2014. Sequence to sequence learning with neural networks. In Neural information processing systems. pages 3104–3112.

R Weide. 1998. The CMU pronunciation dictionary, release 0.6. Carnegie Mellon University.

Lei Yu, Phil Blunsom, Chris Dyer, Edward Grefenstette, and Tomas Kocisky. 2016. The Neural Noisy Channel. arXiv:1611.02554.

Barret Zoph and Kevin Knight. 2016. Multi-source neural translation. arXiv:1601.00710.