Interacting via natural language dialog

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Or
How to talk to customers
(by computer)
Two aspects of talking to customers

2. Generating text in Product Descriptions
Part I: Generating Better Responses from Neural Chatbots

Jiwei Li
Chatbots are everywhere

• Carry on simple fun conversations with customers
• Solve some simple tasks on the side
• State of the art: simple rule-based systems

• Goal: Can we do a better job with generating simple conversational text with machine learning?
Generation Models for Chatbots

What's your favorite chocolate?

I'm very fond of Hershey's with Almonds!
Seq2seq: A recent paradigm for chatbots

• The encoder-decoder or sequence-to-sequence model
• A neural network that maps sentences to sentences
  • Input: the sentence the user just typed
  • Output: the proposed system response
Seq2Seq Models for Response Generation
(Sutskever et al., 2014; Jean et al., 2014; Luong et al., 2015)

Loss = $- \log p(\text{target}|\text{source})$

Source: User's Sentence
Target: What the system should say

I'm fine.
Seq2Seq Models for Response Generation

how are you?
Seq2Seq Models for Response Generation

Encoding

how are you ?
Seq2Seq Models for Response Generation

Encoding

how  are  you  ?
Seq2Seq Models for Response Generation

Encoding

how, are, you, ?
Seq2Seq Models for Response Generation

Encoding

how     are     you     ?
Seq2Seq Models for Response Generation

Encoding

how are you ?

Decoding
Seq2Seq Models for Response Generation
Seq2Seq Models for Response Generation

how are you?

I'm fine

Encoding

Decoding

I'm

eos

fine

how are you?

I'm fine
Seq2Seq Models for Response Generation

how are you?
I’m fine.
Seq2Seq Models for Response Generation

Encoding

how
are
you
?

Decoding

I’m
eos
I’m
fine
.

EOS
Problems with Neural Response Generation: Boring and non-human sentences

<table>
<thead>
<tr>
<th>Input: What are you doing?</th>
<th>Output:</th>
<th>Score</th>
</tr>
</thead>
<tbody>
<tr>
<td>I don’t know.</td>
<td>Get out of here.</td>
<td>-1.09</td>
</tr>
<tr>
<td>I don’t know!</td>
<td>I’m going home.</td>
<td>-1.09</td>
</tr>
<tr>
<td>Nothing.</td>
<td>Oh my god!</td>
<td>-1.09</td>
</tr>
<tr>
<td>Get out of the way.</td>
<td>I’m talking to you.</td>
<td>-1.10</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Input: what is your name?</th>
<th>Output:</th>
<th>Score</th>
</tr>
</thead>
<tbody>
<tr>
<td>I don’t know.</td>
<td>...</td>
<td></td>
</tr>
<tr>
<td>I don’t know!</td>
<td>My name is Robert.</td>
<td>-1.55</td>
</tr>
<tr>
<td>I don’t know, sir.</td>
<td>My name is John.</td>
<td>-1.58</td>
</tr>
<tr>
<td>Oh, my god!</td>
<td>My name’s John.</td>
<td>-1.59</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Input: How old are you?</th>
<th>Output:</th>
<th>Score</th>
</tr>
</thead>
<tbody>
<tr>
<td>I don’t know.</td>
<td>...</td>
<td></td>
</tr>
<tr>
<td>I’m fine.</td>
<td>Twenty-five.</td>
<td>-1.64</td>
</tr>
<tr>
<td>I’m all right.</td>
<td>Five.</td>
<td>-1.66</td>
</tr>
<tr>
<td>I’m not sure.</td>
<td>Eight.</td>
<td>-1.71</td>
</tr>
</tbody>
</table>
Neural Dialogue Systems: Can we generate more human-like responses?

1. **Avoid un-informative, repetitive utterances**
   - Use the MMI Objective to penalize uninformative sentences (Li et al. 2016 "A Diversity-Promoting Objective Function for Neural Conversation Models.")
   - Use a new decoding algorithm that leads to diverse outputs (Li et al. 2017a)
   - Learn the appropriate level of specificity (via reinforcement learning) (Li et al. 2017b)

2. **Jointly maximize dialog forward-looking function, coherence, and informativeness**
   - Via reinforcement learning (Li et al. 2016 "Deep Reinforcement Learning for Dialogue Generation. ")

3. **Generate sentences with better discourse coherence**
   - New latent-variable neural generator (Li and Jurafsky 2017)
Example: encourage diversity in responses
Generating Diverse Responses
A Diversity-promoting Beam Search Algorithm

Standard Beam Search

Diversity Promoting Beam Search (γ set to 1)
A Simple, Fast Diverse Decoding Model for Neural Generation

**Input**  As the joint chief of the eight clans, you should do something.

**Response**

**N-best List (Vanilla Beam Search)**
If you want to fight, you must go to the temple. . . .
if you want to fight, you must go to the temple to fight .
If you want to fight, you must go to the temple. . .
If you want to fight, you must go to the police station .
If you want to fight, you must go to the palace.

**N-best List (Diverse Beam Search)**
If you want to fight, you must go to the temple.
If you want to fight, you can do it yourself.
No, I’m not going to do anything.
I’m not going to let you go, I’m not going to let you do that.
But I don’t want to be a monk
A Simple, Fast Diverse Decoding Model for Neural Generation

Help a variety of generation tasks in NLP

### Dialogue Generation (BLEU)

<table>
<thead>
<tr>
<th>Method</th>
<th>Score</th>
</tr>
</thead>
<tbody>
<tr>
<td>Standard Beam Search</td>
<td>1.88</td>
</tr>
<tr>
<td>Diverse Beam Search</td>
<td>2.21</td>
</tr>
</tbody>
</table>

### Summarization (ROUGE-2)

<table>
<thead>
<tr>
<th>Method</th>
<th>Score</th>
</tr>
</thead>
<tbody>
<tr>
<td>Standard Beam Search</td>
<td>9.3</td>
</tr>
<tr>
<td>Diverse Beam Search</td>
<td>11.0</td>
</tr>
</tbody>
</table>

### Machine Translation (BLEU)

<table>
<thead>
<tr>
<th>Method</th>
<th>Score</th>
</tr>
</thead>
<tbody>
<tr>
<td>Standard Beam Search</td>
<td>21.5</td>
</tr>
<tr>
<td>Diverse Beam Search</td>
<td>22.4</td>
</tr>
</tbody>
</table>
These algorithms indeed all help

Baseline mutual information model
(Li et al. 2015)
A: Where are you going?
B: I’m going to the restroom.
A: See you later.
B: See you later.
A: See you later.
B: See you later.

Reinforcement learning model
(Li et al. 2016)
A: Where are you going?
B: I’m going to the police station.
A: I’ll come with you.
B: No, no, no, no, you’re not going anywhere.
A: Why?
B: I need you to stay here.
A: I don’t know what you are talking about.
But instead of choosing arbitrary criteria:

How about directly optimizing "human-like"

A good dialogue model should generate utterances indistinguishable from human dialogues.
Adversarial Learning for Neural Dialogue Generation
Jiwei Li, Will Monroe, Tianlin Shi, Alan Ritter, and Dan Jurafsky

Given a question "How are you?"

1) Generator Model generates a response
   "I’m fine"

2) Discriminator Model tries to tell if it's human or machine
   P= 90% human generated
   "I’m fine"
   P= 10% machine generated

3) Use success at fooling discriminator as reward for training the Generator
   😊
Adversarial Learning for Neural Dialogue Generation

**Generative Model (G)**

- **Encoding**
  - how
  - are
  - you
  - ?

- **Decoding**
  - eos
  - I'm
  - fine

- **EOS**

**Discriminative Model (D)**

- **Reward**
  - P= 90% human generated

- **how**
- **are**
- **you**
- **?**
- **eos**
- **I’m**
- **fine**
- **.**
Adversarial Evaluation: "Adversarial Success"

How often a system can fool a computer into believing that its generated response was from a human

How are you?

I don't know

The machine evaluator is fooled!!!

I think "P= 90% human generated"
Results: Adversarial Learning Improves Response Generation

vs a vanilla generation model

<table>
<thead>
<tr>
<th></th>
<th>Adversarial Win</th>
<th>Adversarial Lose</th>
<th>Tie</th>
</tr>
</thead>
<tbody>
<tr>
<td>Adversarial</td>
<td>62%</td>
<td>18%</td>
<td>20%</td>
</tr>
<tr>
<td>Adversarial</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Learning</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Standard Seq2Seq model</td>
<td>8.0</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Machine Evaluator</td>
<td>4.9</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Adversarial Success
(How often can you fool a machine)
Tell me ... how long have you had this falling sickness?

<table>
<thead>
<tr>
<th>System</th>
<th>Response</th>
</tr>
</thead>
<tbody>
<tr>
<td>Vanilla-MLE</td>
<td>I’m not a doctor.</td>
</tr>
<tr>
<td>Vanilla-Sample</td>
<td>Well everything you did was totally untrue.</td>
</tr>
<tr>
<td>REINFORCE</td>
<td>I don’t know how long it’s been.</td>
</tr>
<tr>
<td>REGS Monte Carlo (Reward for Every Generation Step)</td>
<td>A few months, I guess.</td>
</tr>
</tbody>
</table>
But this is just pure chatting!
What about **task-based** dialogue?

Can these simple encoder-decoder models handle actual tasks like restaurant recommendation?
A Copy-Augmented Sequence-to-Sequence Architecture Gives Good Performance on Task-Oriented Dialogue

Mihail Eric and Christopher Manning
Hi, what can I help you with?

I’m feeling Italian

There are 3 Italian restaurants nearby

Hmm… actually any froyo around?

No froyo, sadly, but there is a gelato cafe

Cool! Where is it?
Sequence-to-Sequence models with attention
Innovation: Copy-Augmented Seq2Seq

- Add "copy" mechanism as an option to generator
- Known to improve machine translation, text summarization

Is there cheap italian food → Buca di Beppo is an italian restaurant that is cheap
Experiment

• Data:
  • Dialogue State Tracking Challenge 2 (DSTC2)
  • Restaurant Reservation Domain
  • 1600 Dialogues

• Train:
  • Seq2seq model to predict system from user
Innovations

1. Copy-augmented sequence-to-sequence
2. Give the system extra information about the entity type of the words (restaurant, address, etc.)
System output: seq2seq plus copying

User: cheap restaurant in east part of town
System: api call r cuisine east cheap
User: <silence>
System: the missing sock is a nice place in the east of town and the prices are cheap
User: address
System: sure, the missing sock is on [the_missing_sock_address]
User: phone number
System: the phone number of the missing sock is [the_missing_sock_phone]
User: thank you good bye
System: you are welcome
Dialogue using sequence-to-sequence models

• Still not commercial quality
  • Currently too fragile
  • Commercial systems are still using simple machine learning for understanding user queries
  • And using "templated generation" (each sentence hand-written)

• Nonetheless a very exciting direction!!
Part II: How to talk to customers without dialog
Motivation: How to sell healthy food
What's on "healthy" menus?

<table>
<thead>
<tr>
<th>Not on healthy menus</th>
</tr>
</thead>
<tbody>
<tr>
<td>Indulgent</td>
</tr>
<tr>
<td>bliss, indulge, richest, succulent, decadent</td>
</tr>
<tr>
<td>Exciting</td>
</tr>
<tr>
<td>crazy, temptation, action, adventure, fiery</td>
</tr>
<tr>
<td>Sensory</td>
</tr>
<tr>
<td>delicious, salty, tangy, creamy, crunchy</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>On healthy menus</th>
</tr>
</thead>
<tbody>
<tr>
<td>Nutrients</td>
</tr>
<tr>
<td>carb, fiber, fat, grain, protein, whole wheat</td>
</tr>
<tr>
<td>Deprivation</td>
</tr>
<tr>
<td>light, fat free, low-fat, sugar-free, low carb</td>
</tr>
<tr>
<td>Simple</td>
</tr>
<tr>
<td>simple, dry, mild, plain, mildly, simply</td>
</tr>
</tbody>
</table>

Product descriptions matter!

What about other products?

What language in online product descriptions lead to higher sales?
Collaboration with e-commerce site Rakuten

• Rakuten hosts many different vendors
  • Selling the identical brand product
  • But with different product descriptions
• A natural experiment: what language leads to different sales?
Which words lead to greater sales:

**Chocolate**

**Health**
Which will sell more?

A

Royce’s chocolate has become a standard Hokkaido souvenir. They are packaged one by one so your hands won’t get dirty! Also, our staff recommends this product!

北海道のお土産で定番品となっているロイズ。手が汚れないように1本ずつパッケージされているのもありかい! 当店スタッフもおすすめするロイズの自信作です!

B

Four types of nuts: almonds, cashews, pecans, macadamia, as well as cookie crunch and almond puff were packed carefully into each chocolate bar. This item is shipped with a refrigerated courier service during the summer.

アーモント、カシューハーゲン、マカタミアの4種類のナッツとクッキークランチやアーモントパフを一本のチョコレートバーにきっちり詰め込みました。こちらは夏期クール便発送商品です。
Training: 100,000 items from 2012 snapshot

<table>
<thead>
<tr>
<th></th>
<th>Chocolate</th>
<th>Health</th>
</tr>
</thead>
<tbody>
<tr>
<td># Items</td>
<td>32,104</td>
<td>61,487</td>
</tr>
<tr>
<td># Vendors</td>
<td>1373</td>
<td>1533</td>
</tr>
<tr>
<td>Words (tokens)</td>
<td>6,581,490</td>
<td>16,706,646</td>
</tr>
</tbody>
</table>
Testing: 2,131 hand-labeled products

<table>
<thead>
<tr>
<th></th>
<th>Chocolate</th>
<th>Health</th>
</tr>
</thead>
<tbody>
<tr>
<td># Items</td>
<td>924</td>
<td>1207</td>
</tr>
<tr>
<td># Products</td>
<td>186</td>
<td>50</td>
</tr>
<tr>
<td># Vendors</td>
<td>201</td>
<td>384</td>
</tr>
<tr>
<td>#items per product</td>
<td>4</td>
<td>9</td>
</tr>
</tbody>
</table>
How to find words that are good predictors of sales

• Prior method: Feature Selection
  • Odds ratio
  • Mutual information
  • Lasso (L1 regularization)
    • Run a regression to predict sales from words
    • Chose all the words with high weights
Problem with these kinds of feature selection

- The words that best predict sales are exactly the words the seller can't change!
- Highest weighted features from Lasso, Mutual Information, Odds Ratio:
  - Words that are the name of the vendor
  - Words that are part of the brand name
  - Words from the vendor address
  - Words indicating price ("bargain")
New idea: Adversarial Networks

• Problem: Other algorithms discover words that are too correlated with brand or price
• Solution:
  • Build a feature-selecting neural network that estimates sales, brand, and price
  • Train the model to be
    • **good** at predicting sales
    • **bad** at predicting brand and price
  • Use model's "attention" weights to find good feature words
An RNN good at predicting sales and bad at predicting price or brand

Figure 1: An illustration of the proposed RNN+GF model operating on an example product description with three timesteps. All operations and dimensionalities are explicitly shown. Vectors are depicted as rounded rectangles, matrix multiplications as squared rectangles, and scalars as circles. Trainable parameters are grey, while dynamically computed values are colored. Gradient reversal layers multiply gradients by -1 as they backpropagate from the prediction networks to the encoder. In this example, the model attends to the description's final token the most, so that would be the most likely candidate for a generated lexicon.

Table 1: Characteristics of the Rakuten data. These data consist of 93,591 product descriptions, brands, prices, and sales figures. Notably, the ratio of the size of vocabulary (unique keywords) to the size of tokens (occurrence of keywords) in the chocolate category is twice as large as that of the health category as listed in (%) in Table 1. This implies that product descriptions in the chocolate category are written with more diverse language.

Table 2: Characteristics of test sets. Product labels were manually assigned to these data for evaluation purposes.
We included the aforementioned linguistic features as Table 3: Average association strengths between each BPE features, and the confounding product/vendor labels in the test set. Our results suggest that this decorrelation is due to the gradient clipping mechanism. When the gradient is ablated, the resulting model selects the confound-correlated features. This finding features that are simultaneously explanatory of sales and untangled from the confounding effects of product, brand, and price. Table 3 indicates that the RNN+GF features are less correlated with these confounds than any other method. Furthermore, the RNN-GF model is fitted with the top 500 features from each approach. Overall, these results strongly support the hypothesis that narrative elements of product descriptions are predictive of consumer behavior (many of which are depicted in Figure 2).


<table>
<thead>
<tr>
<th>Feature Selection Method</th>
<th>Chocolate</th>
<th>Health</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lasso</td>
<td>0.44</td>
<td>0.44</td>
</tr>
<tr>
<td>Mutual Information</td>
<td>0.44</td>
<td>0.44</td>
</tr>
<tr>
<td>Lasso + MI</td>
<td>0.44</td>
<td>0.44</td>
</tr>
<tr>
<td>RNN+GF</td>
<td>0.78</td>
<td>0.44</td>
</tr>
</tbody>
</table>

Selected words help predict sales

**Selected words help predict sales**

- **Chocolate**: Price + Product + Brand + Words
- **Health**: Price + Product + Brand + Words
Selected words have higher correlation with sales

While being less correlated with price, brand, product
Features associated with higher sales

Appeals to authority
"staff" (スタッフ), “old-standing shop” (老舗), and “founded since” (創業),

Politeness
Honorifics and polite verb markers “ing” (しており), “will do” (致します),
“receive” (いたたぐ)

Seasonality
“Christmas” (クリスマス), “year-end gift” (歳暮)

Informativeness
Function ("souvenir"), delimiters indicating structured information ("” 【"”,
“★”, “●”), and detail words (”x2”, “70%”, etc.)
Which will sell more?

A

Royce’s chocolate has become a standard Hokkaido souvenir. They are packaged one by one so your hands won’t get dirty! Also, our staff recommends this product!

B

Four types of nuts: almonds, cashews, pecans, macadamia, as well as cookie crunch and almond puff were packed carefully into each chocolate bar. This item is shipped with a refrigerated courier service during the summer.

北海道のお土産て定番品となっているロイ ス. 手が汚れないように1本ずつハッケージされているのもありだい! 当店スタッフもおすすめするロイスの自信作です!

アーモント、カシュー、ヘガン、マカダミアの4種類のナッツとクッキークランチやアーモントパフを一本のチョコレートバーにきつしり詰め込みました。こちらは夏期クール便発送商品です。
Which will sell more?

A
Royce’s chocolate has become a **standard** Hokkaido **souvenir**. They are packaged one by one so your hands won’t get dirty! Also, our **staff** recommends this product!

B
Four types of nuts: almonds, cashews, pecans, macadamia, as well as cookie crunch and almond puff were packed carefully into each chocolate bar. This item is shipped with a refrigerated courier service during the **summer**.

北海道のお土産定番品となっているロイス。手が汚れないように1本ずつハッケースされているのもありがたい！当店スタッフもおすすめするロイスの自信作です！

アーモント、カシューヘーガン、マカダミアの4種類のナッツとクッキークランチやアーモントパフを一本のチョコレートバーにぎゅしり詰め込みました。こちらは夏期クール便発送商品です。
How to talk to your customers

• Seq2seq neural networks are a promising but not yet mature technology for dialogue
• Neural networks can also help with analytics
  • Association between language of product descriptions and sales
• Language matters!