

# RNN's Applications

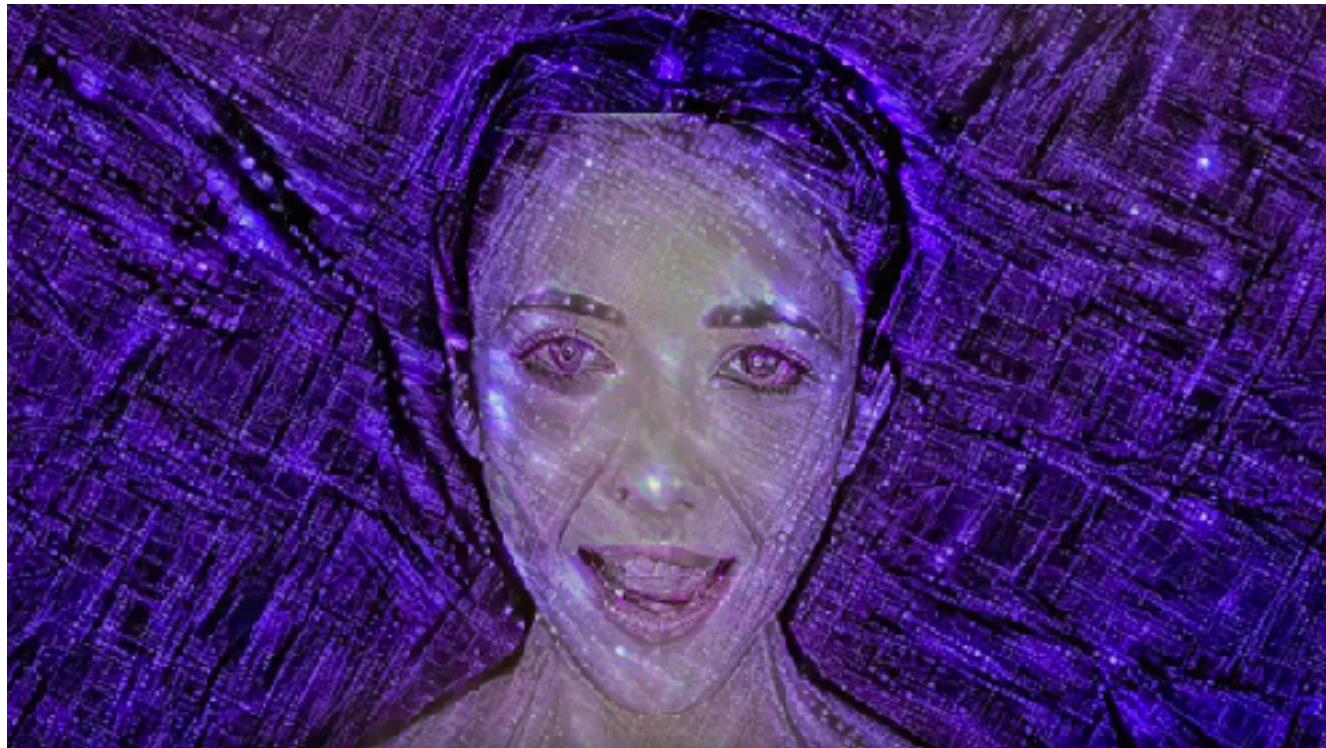
Pramod Kompalli  
OLA

# Sunspring



<https://arstechnica.com/gaming/2016/06/an-ai-wrote-this-movie-and-its-strangely-moving/>

# Generating Music



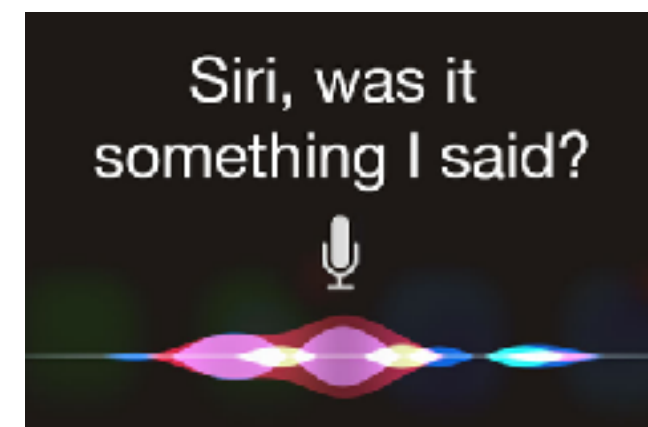
**Break Free**

<https://www.youtube.com/watch?v=XUs6CznN8pw>



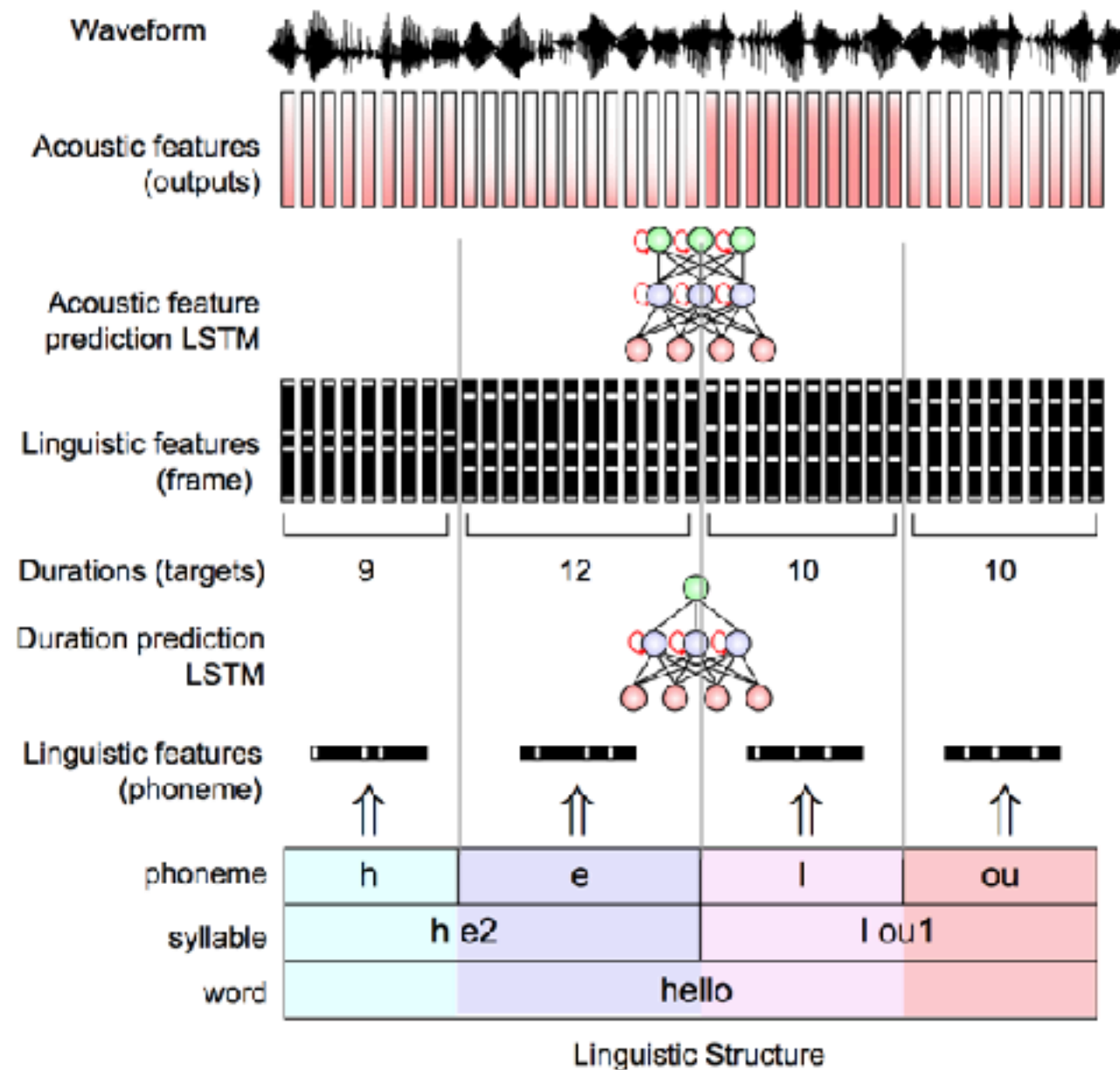
**Deep Music  
@ Alexa**

# Generating Speech



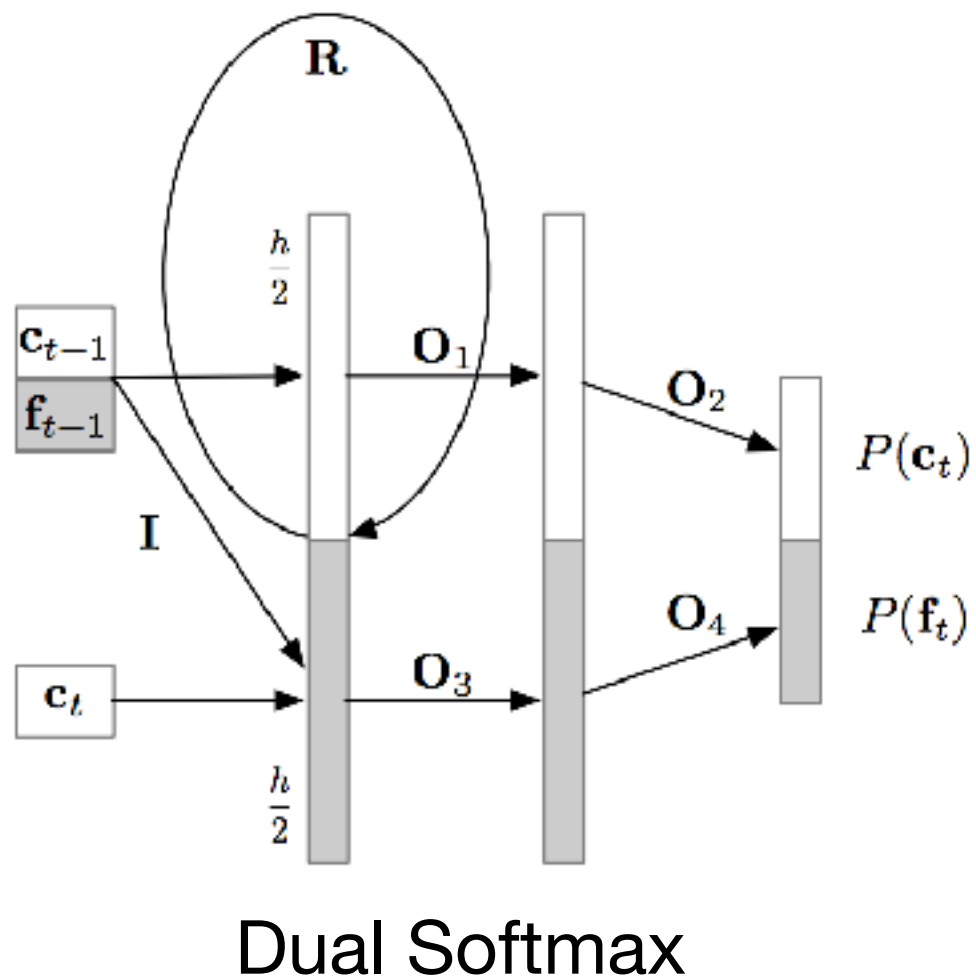


# Generating Speech



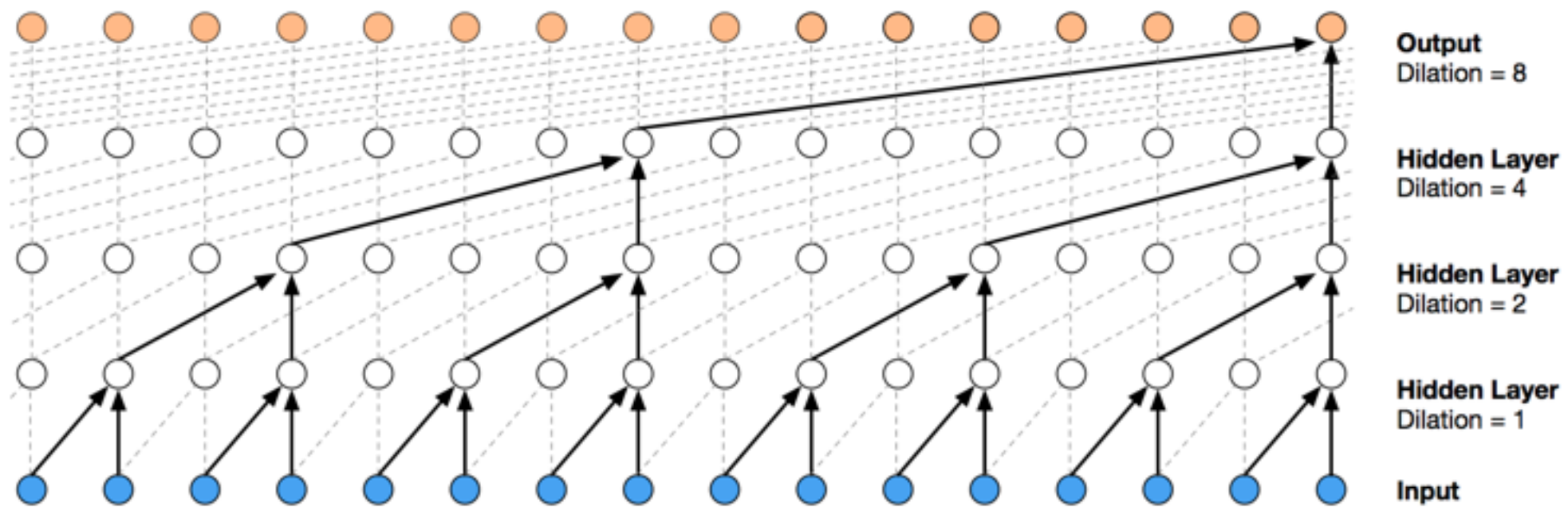
Zen et al., Fast, compact, and high quality LSTM-RNN based statistical parametric speech synthesizers for mobile devices, Interspeech, 2016.

# Generating Speech



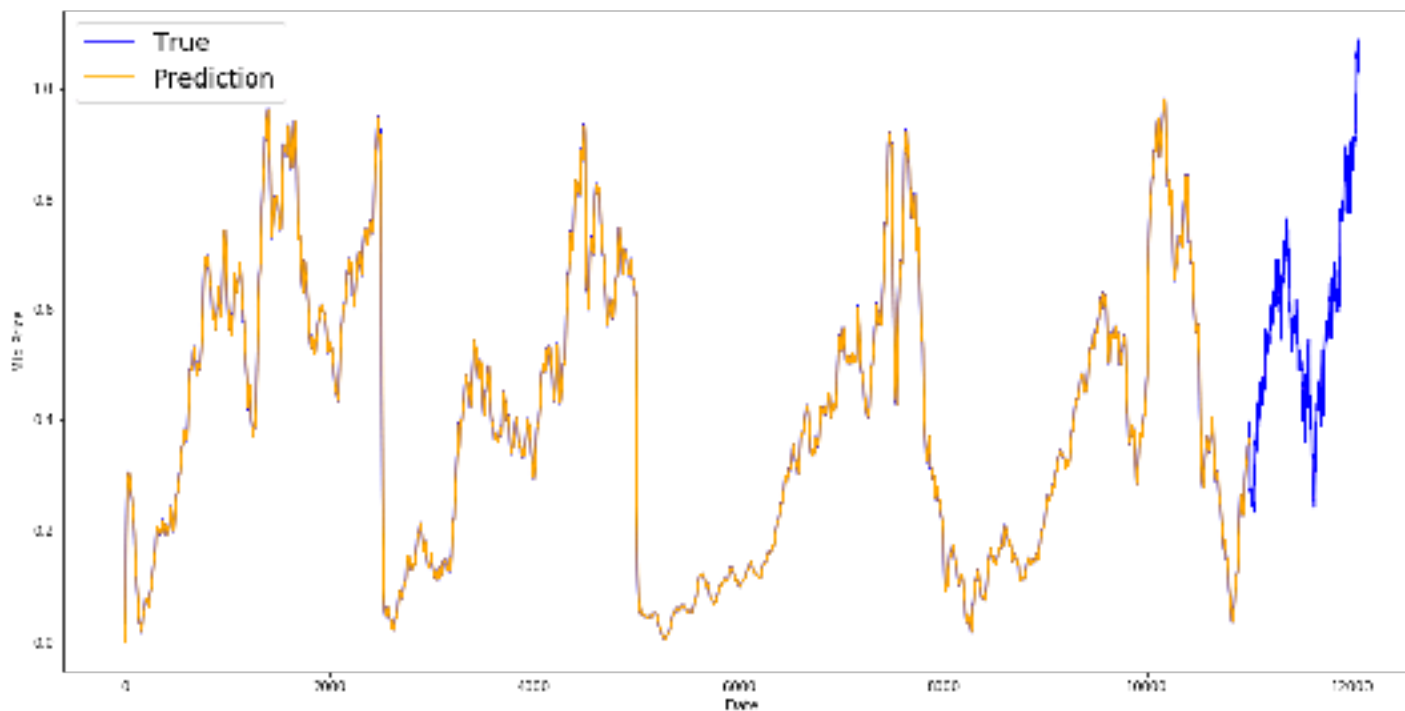
c - coarse bits of audio  
f - fine bits of audio

# Generating Speech



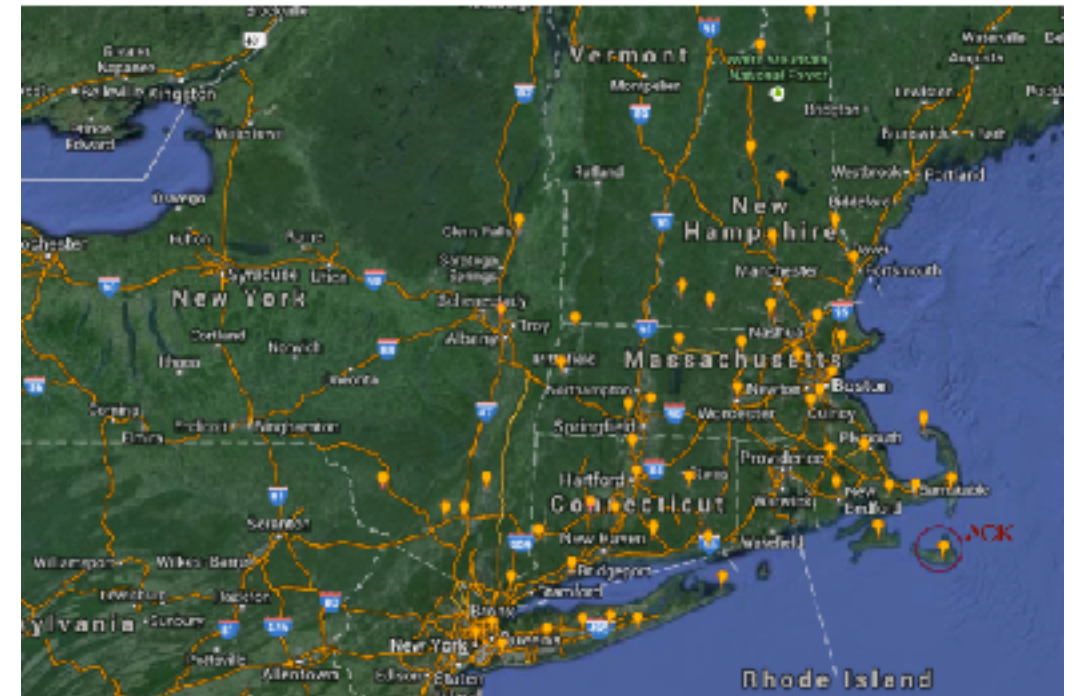
Dilated Convolutions

# Time-Series Predictions



Stock Market Prediction

Nelson et al., Stock market's price movement prediction with LSTM neural networks, IJCNN 2017

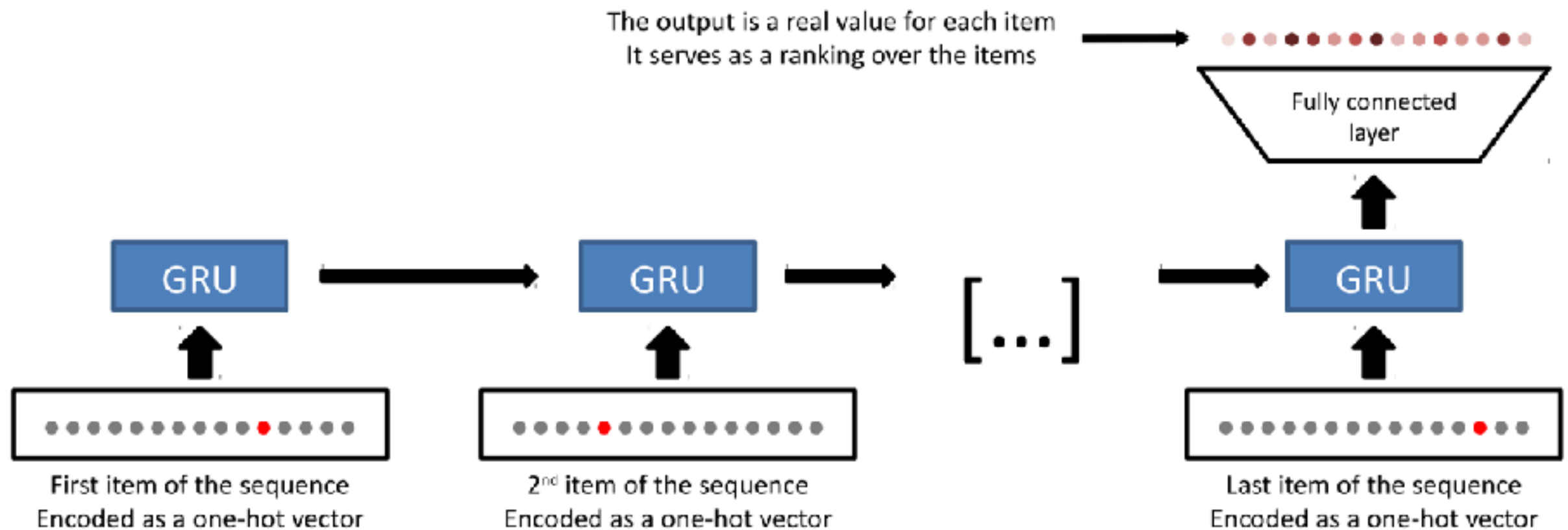


Wind Prediction

Ghaderi et al., Deep Forecast: Deep Learning-based Spatio-Temporal Forecasting, ICML Time series Workshop 2017



# Product Recommendation



Devooght & Bersini, Long and Short-Term Recommendations with Recurrent Neural Networks, UMAP 2017

# Forecasting in eCommerce



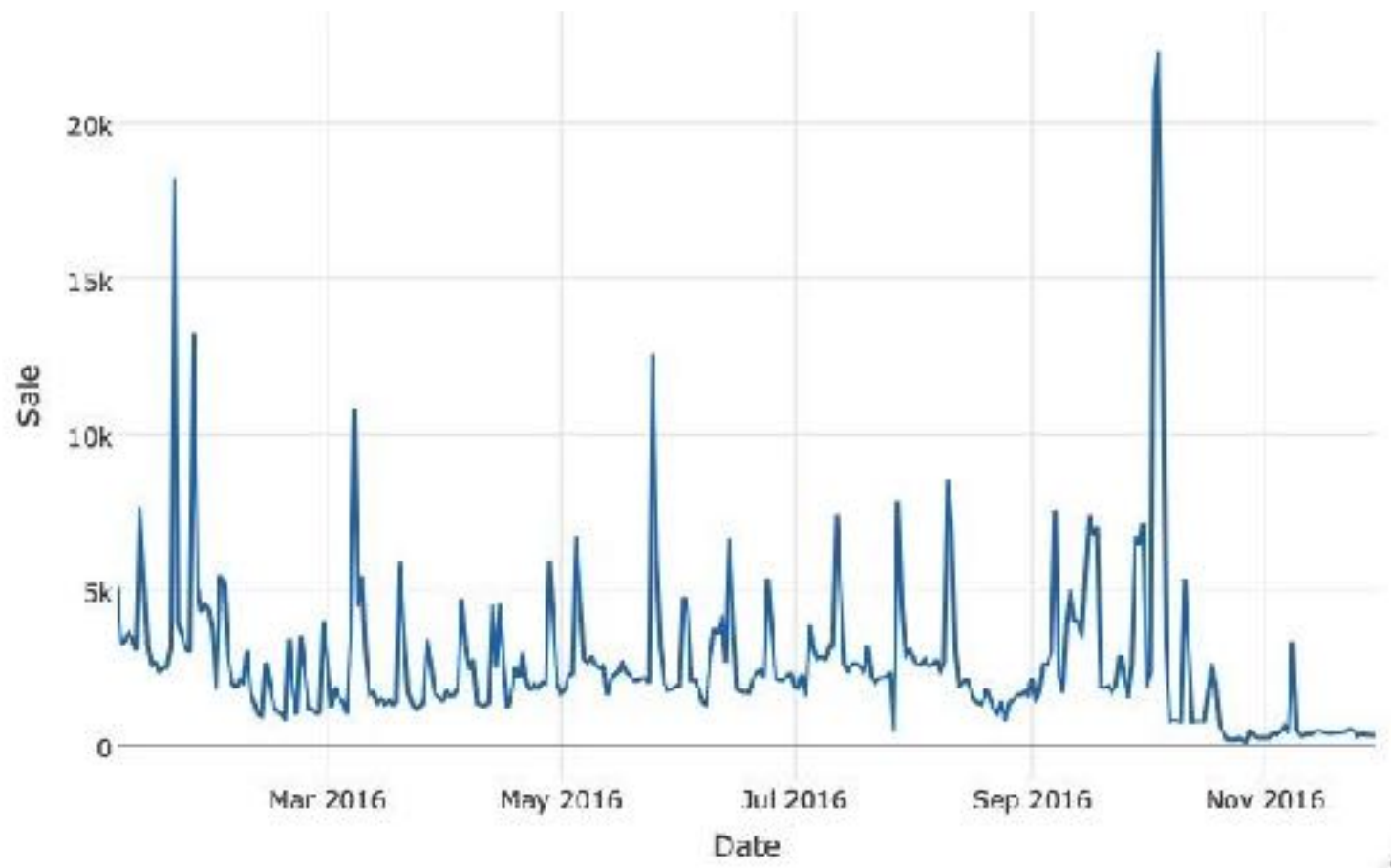
Demand Forecasting

Seasonal  
Demand/Supply



Demand & Supply Forecasting  
Consequently Pricing

# Demand Forecasting @ Flipkart

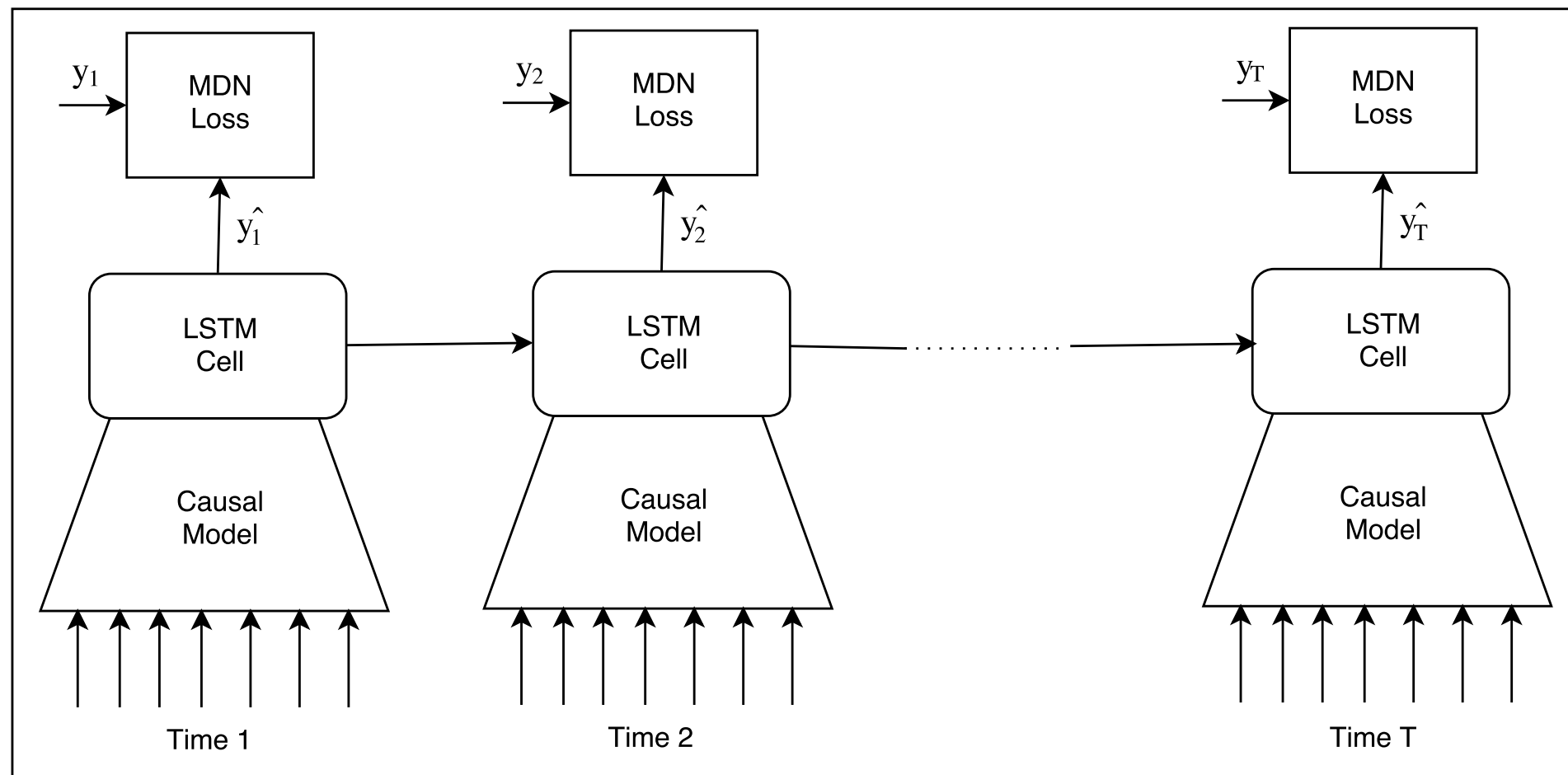


SAMSUNG 32GB Memory Card

- High Variance
- “Causal” factors.
- Dependence on Other products - Upsell & Cannibalisation
- New products have NO history
- Imbalanced data

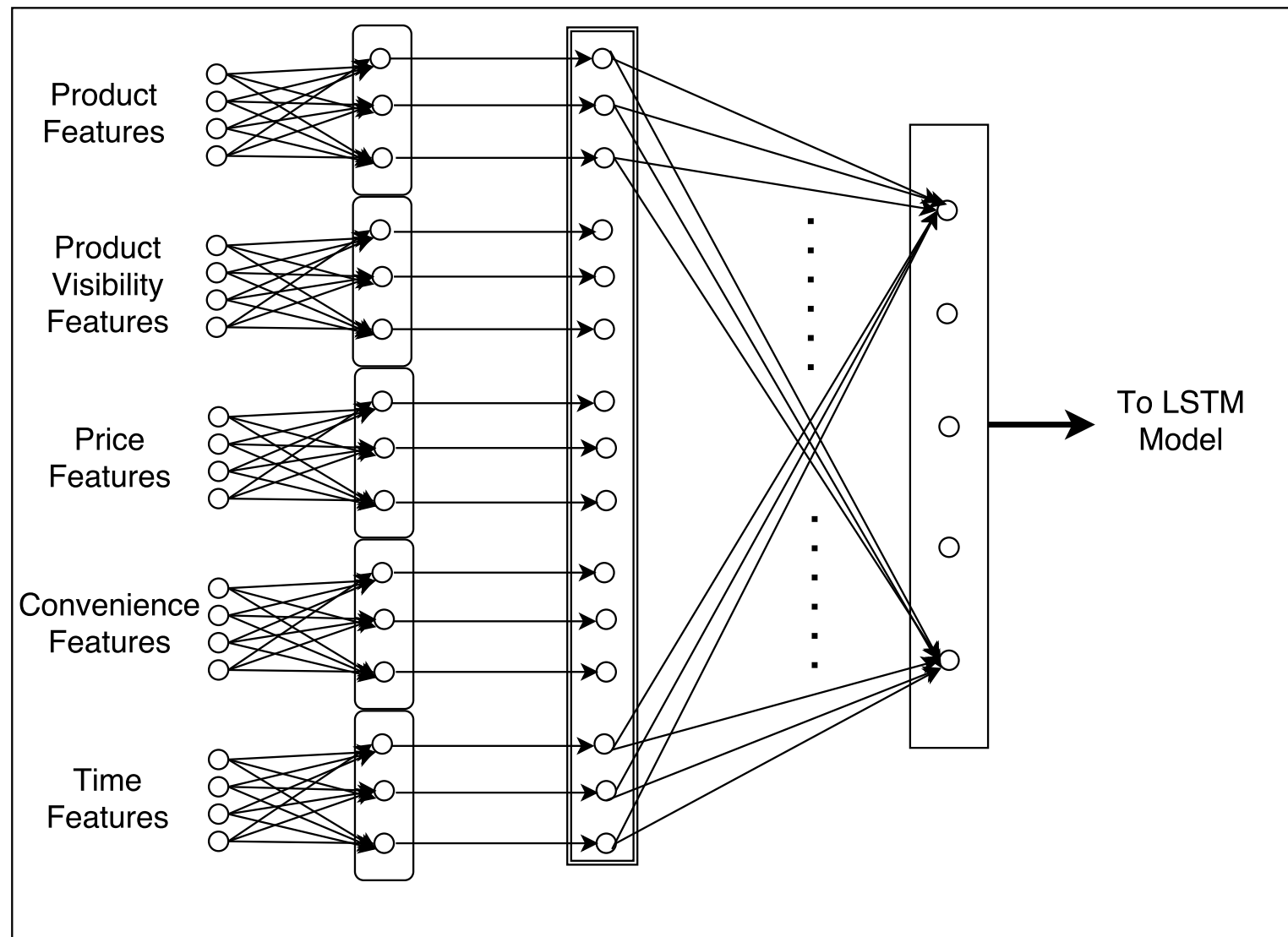
Mukherjee et al., ARMDN: Associative and Recurrent Mixture Density Networks for eRetail Demand Forecasting, *arXiv:1803.03800*

# Demand Forecasting @ Flipkart



Mukherjee et al., ARMDN: Associative and Recurrent Mixture Density Networks for eRetail Demand Forecasting, *arXiv:1803.03800*

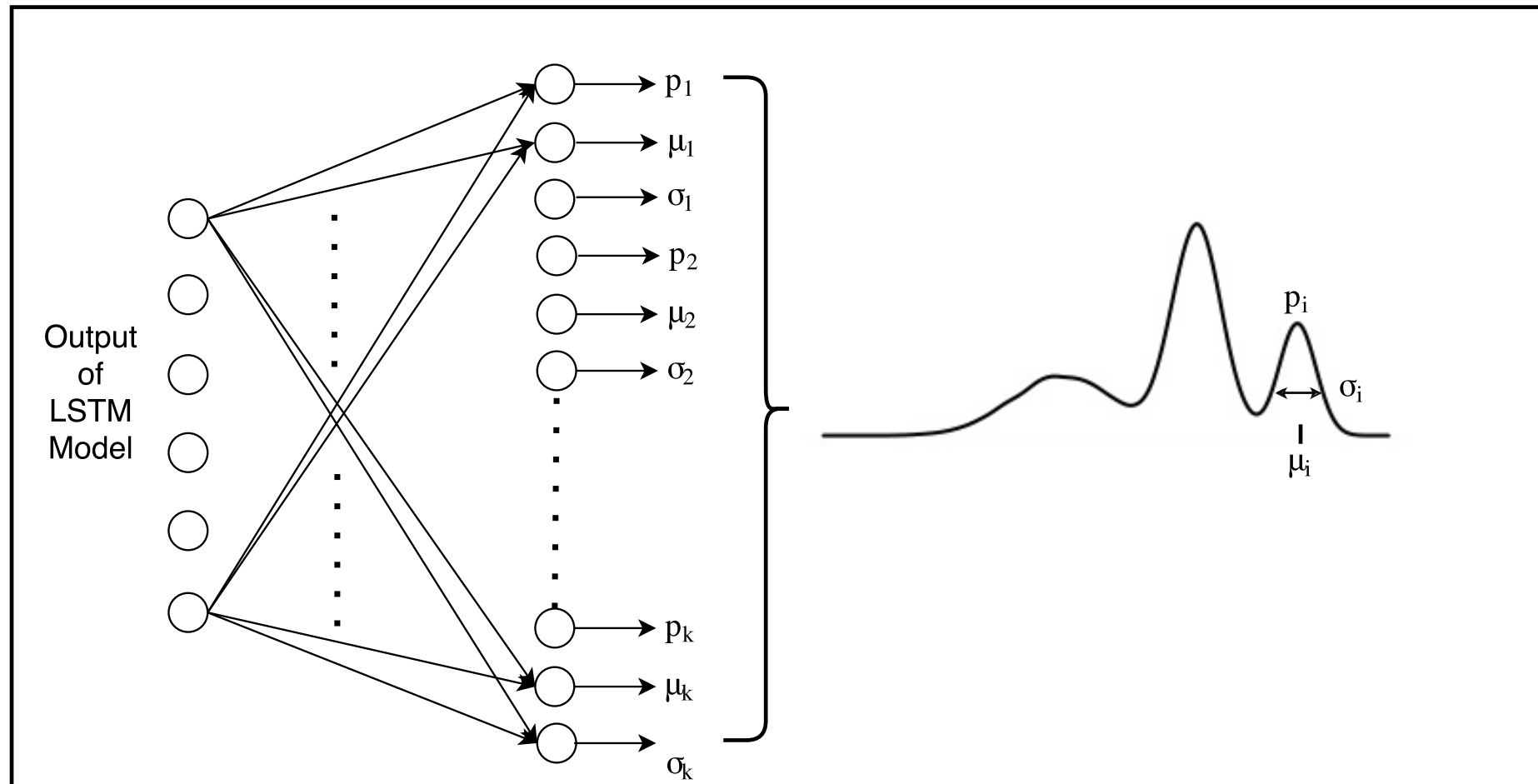
# Demand Forecasting @ Flipkart



Mukherjee et al., ARMDN: Associative and Recurrent Mixture Density Networks for eRetail Demand Forecasting, *arXiv:1803.03800*



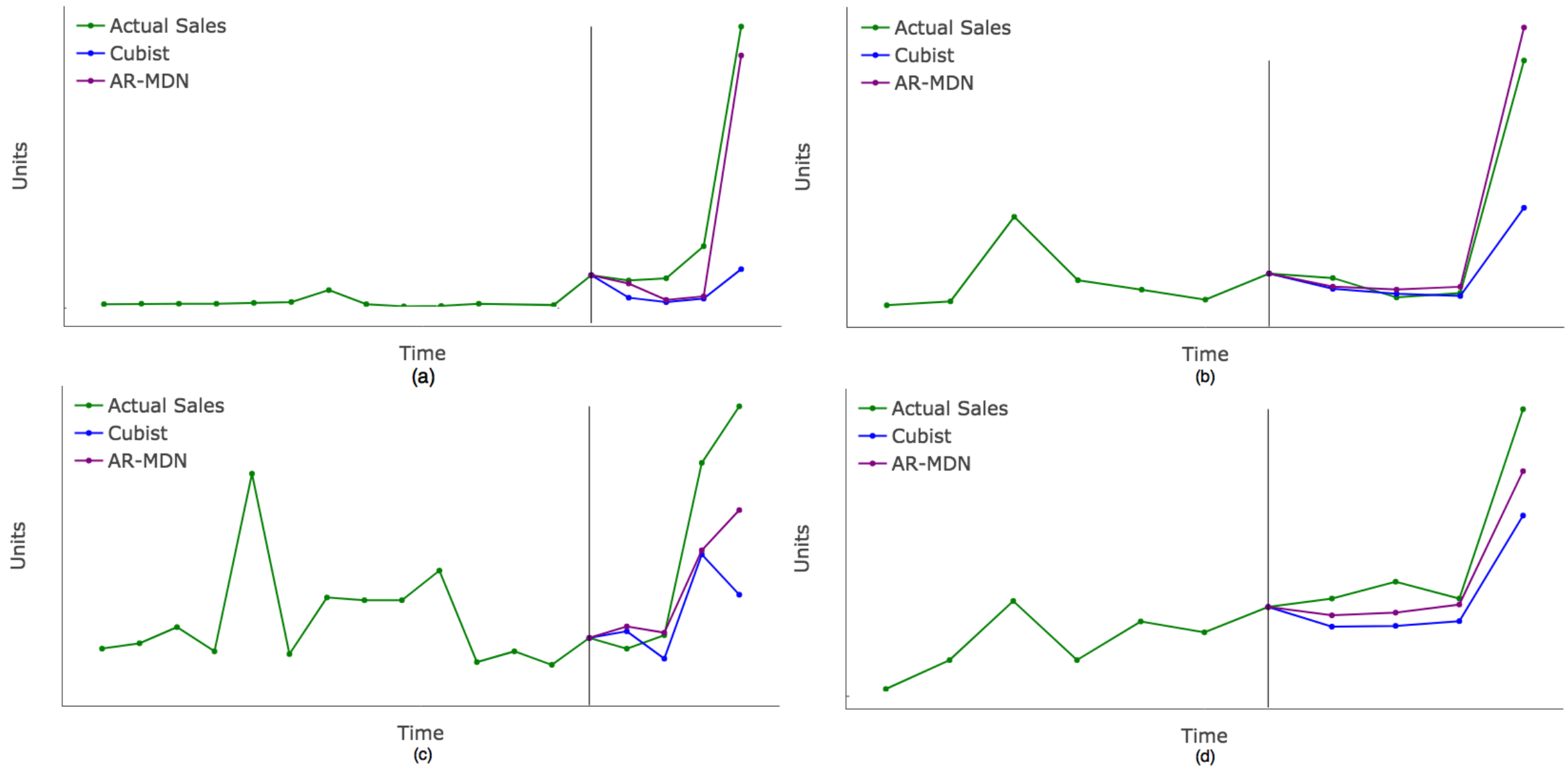
# Demand Forecasting @ Flipkart



$$l_{\text{MDN}}(y|\theta) = -\frac{1}{T} \sum_{j=1}^T \log \sum_{k=1}^K \frac{p_k}{\sqrt{2\pi\sigma_k^2}} \exp\left(-\frac{(y_j - \mu_k)^2}{2\sigma_k^2}\right)$$

Mukherjee et al., ARMDN: Associative and Recurrent Mixture Density Networks for eRetail Demand Forecasting, *arXiv:1803.03800*

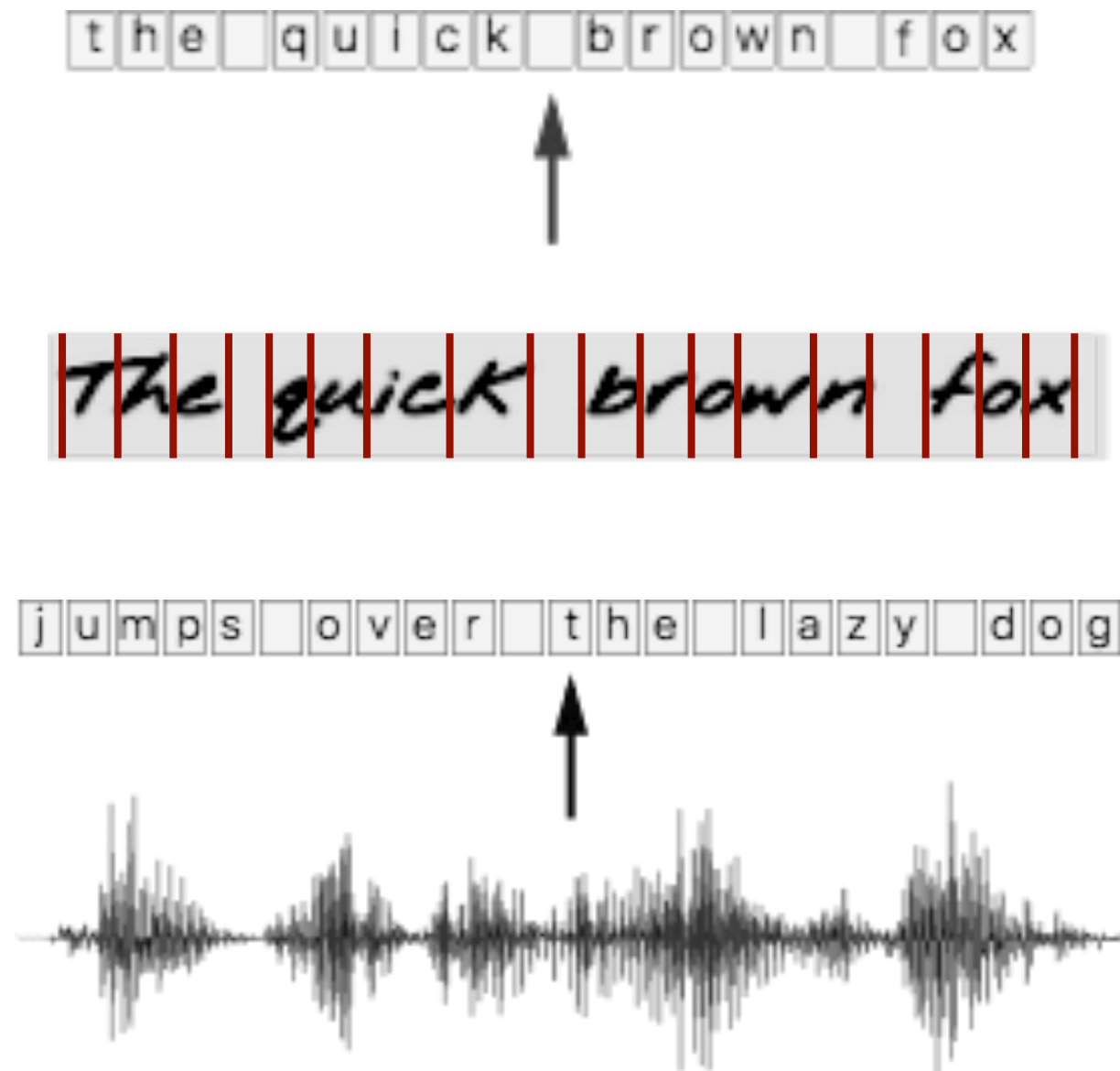
# Demand Forecasting @ Flipkart



wMAPE: 32 (ARMDN) vs 40 (Cubist)

Mukherjee et al., ARMDN: Associative and Recurrent Mixture Density Networks for eRetail Demand Forecasting, *arXiv:1803.03800*

# Sequence Alignment



# S2S Challenges

- Input & Output need not be of same length
- Input & Output need not be aligned
- Input & Output might have different order (before/after)
- Current output depends on previous output
- Dependencies could be of variable length

# Connectionist Temporal Classification (CTC)

 $x_1$   $x_2$   $x_3$   $x_4$   $x_5$   $x_6$ 

input ( $X$ )

c c a a a t

alignment

c a t

output ( $Y$ )

h h e  $\epsilon$   $\epsilon$  | | |  $\epsilon$  | | o

First, merge repeat characters.

h e  $\epsilon$  |  $\epsilon$  | o

Then, remove any  $\epsilon$  tokens.

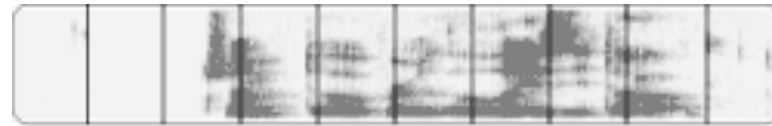
h e | | o

The remaining characters are the output.

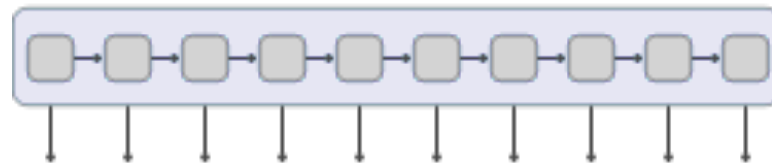
h e l l o



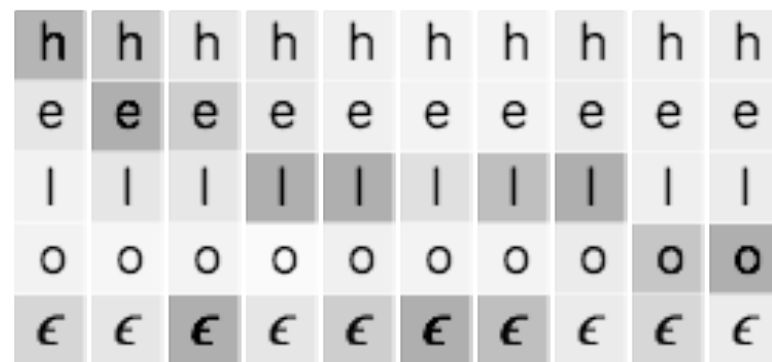
# Connectionist Temporal Classification (CTC)



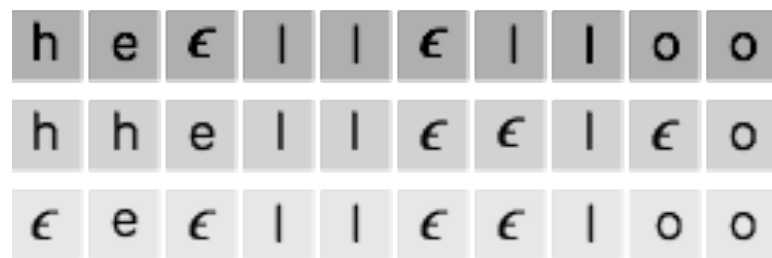
We start with an input sequence, like a spectrogram of audio.



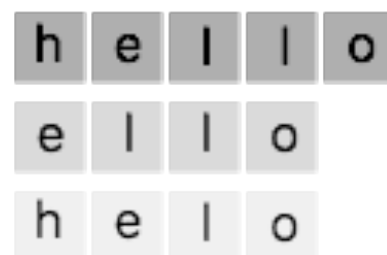
The input is fed into an RNN, for example.



The network gives  $p_t(a | X)$ , a distribution over the outputs  $\{h, e, l, o, \epsilon\}$  for each input step.



With the per time-step output distribution, we compute the probability of different sequences:



By marginalizing over alignments, we get a distribution over outputs

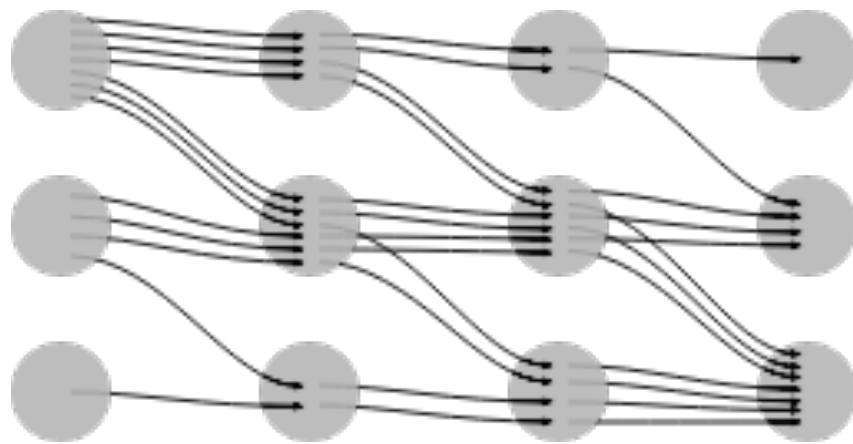
# Connectionist Temporal Classification (CTC)

$$p(Y | X) = \sum_{A \in \mathcal{A}_{X,Y}} \prod_{t=1}^T p_t(a_t | X)$$

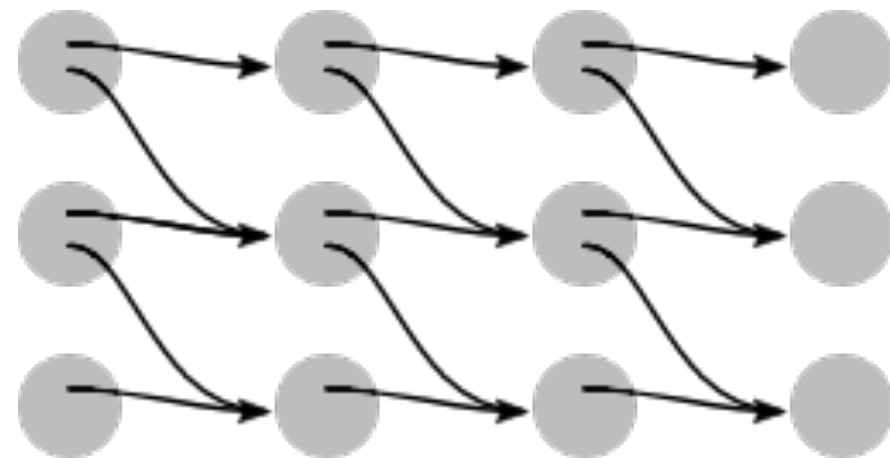
The CTC conditional **probability**

**marginalizes** over the set of valid alignments

computing the **probability** for a single alignment step-by-step.

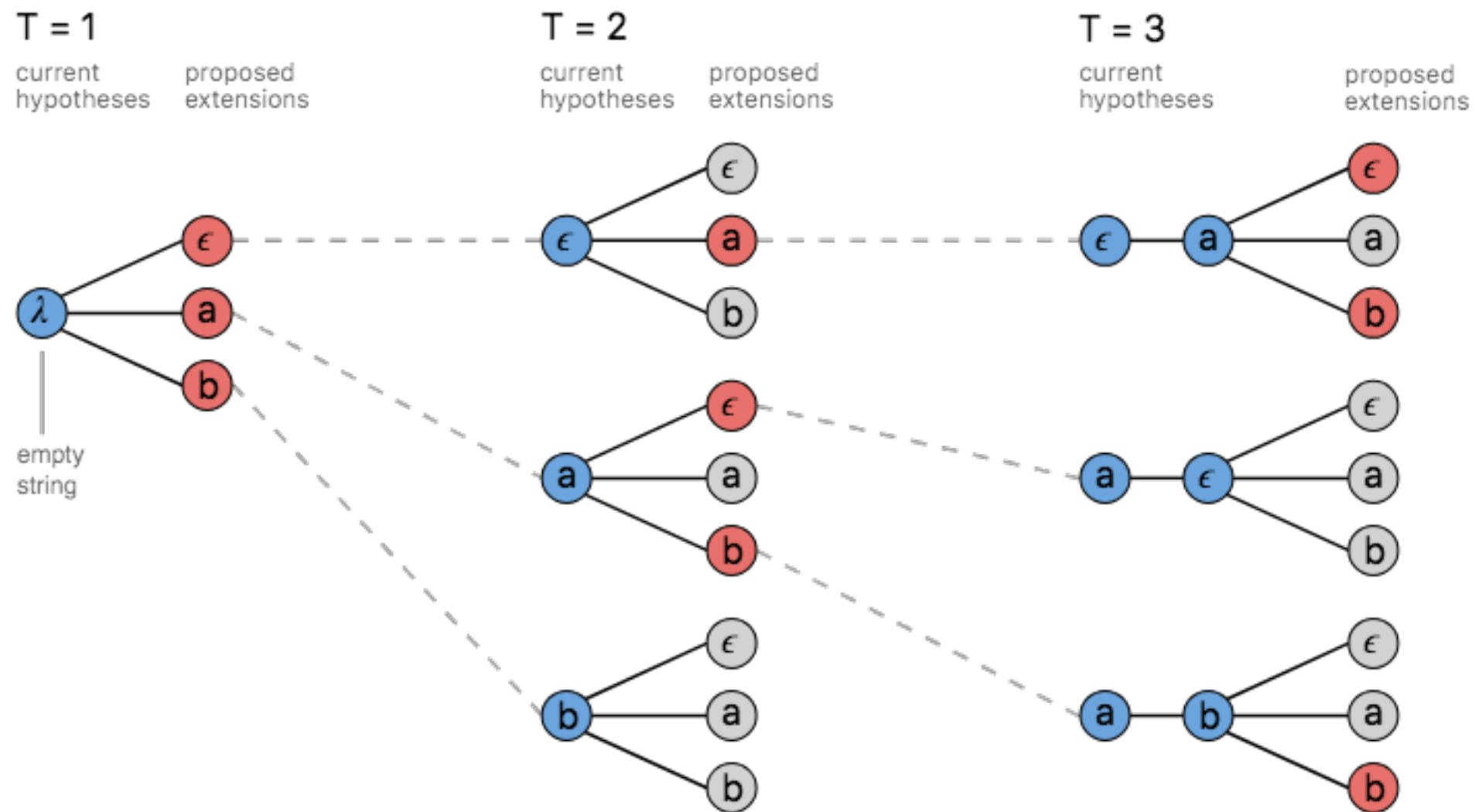


Full-fledged Search



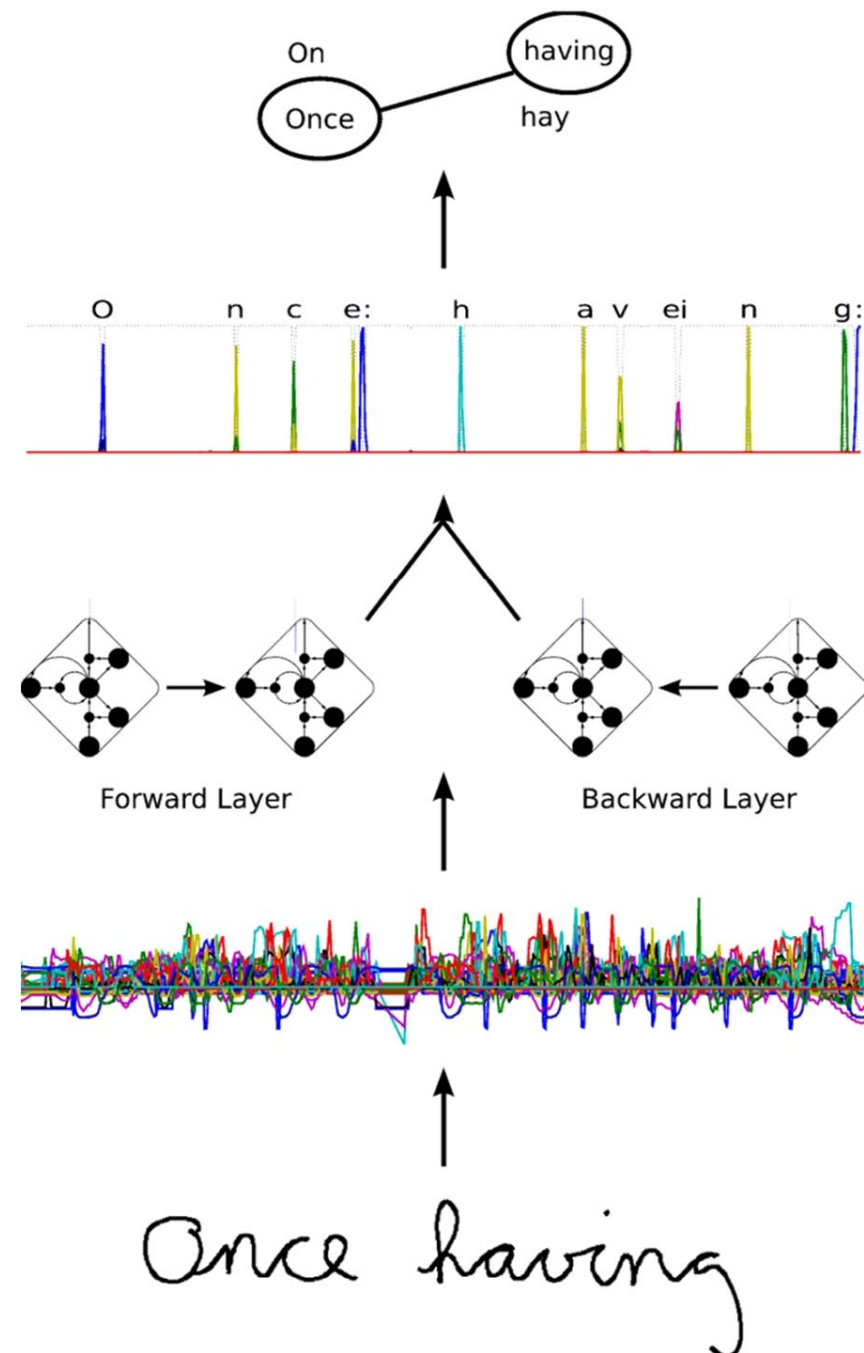
Dynamic Programming

# Connectionist Temporal Classification (CTC)



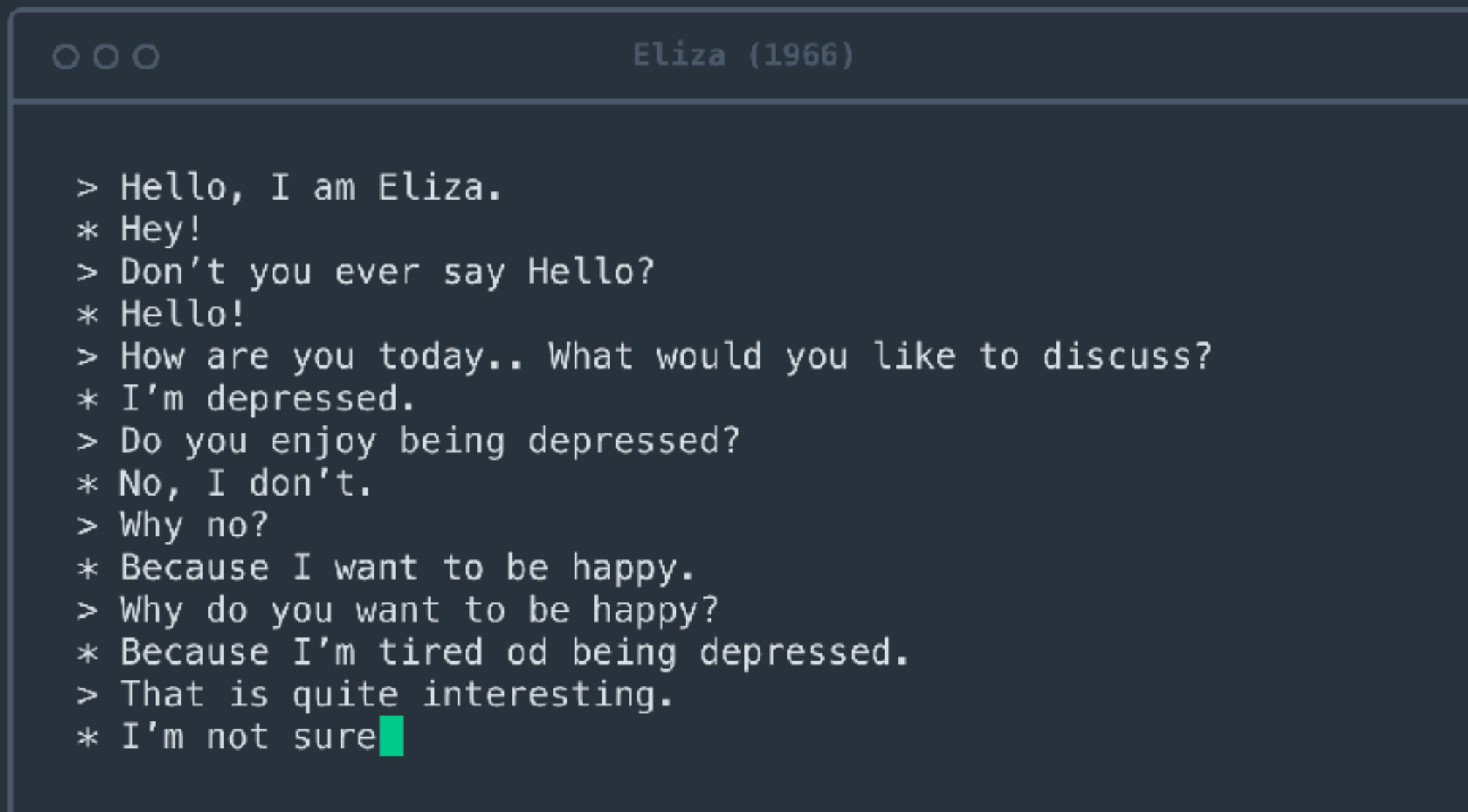
Beam Search

# Handwriting Recognition



Picture courtesy: Marcus Liwicki

# Chat Bots

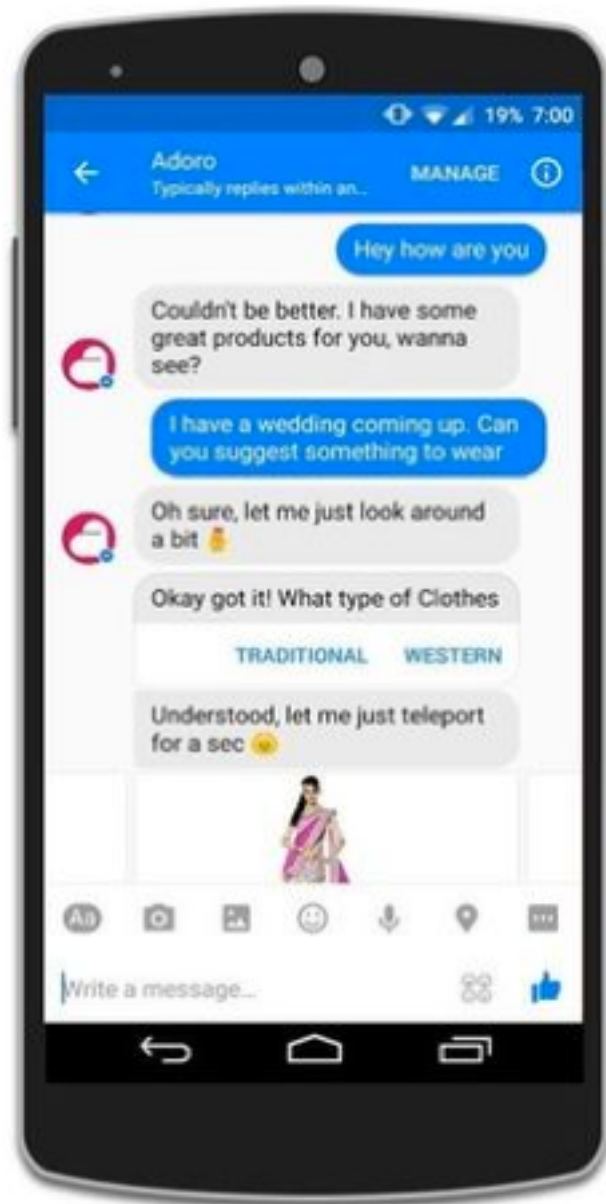


```
Eliza (1966)

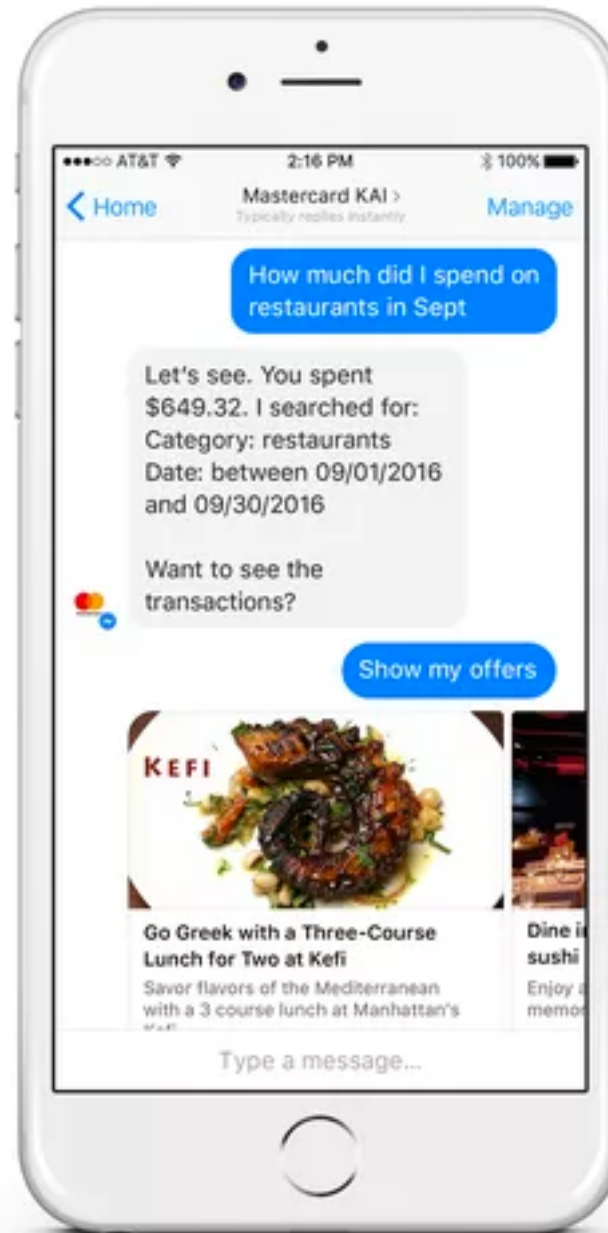
> Hello, I am Eliza.
* Hey!
> Don't you ever say Hello?
* Hello!
> How are you today.. What would you like to discuss?
* I'm depressed.
> Do you enjoy being depressed?
* No, I don't.
> Why no?
* Because I want to be happy.
> Why do you want to be happy?
* Because I'm tired of being depressed.
> That is quite interesting.
* I'm not sure
```



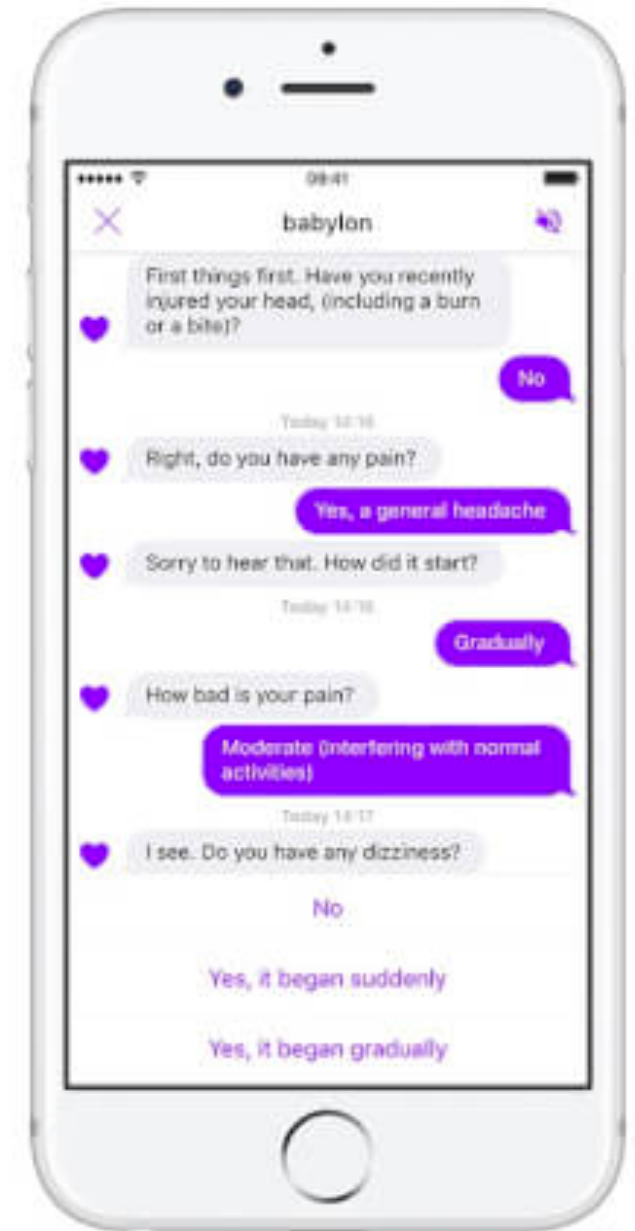
# Chat Bots



eCommerce



Financial



Healthcare

# Chat Bots

**INPUT:** *Hi!*

**OUTPUT:** *Hi!*

**INPUT:** *How are you?*

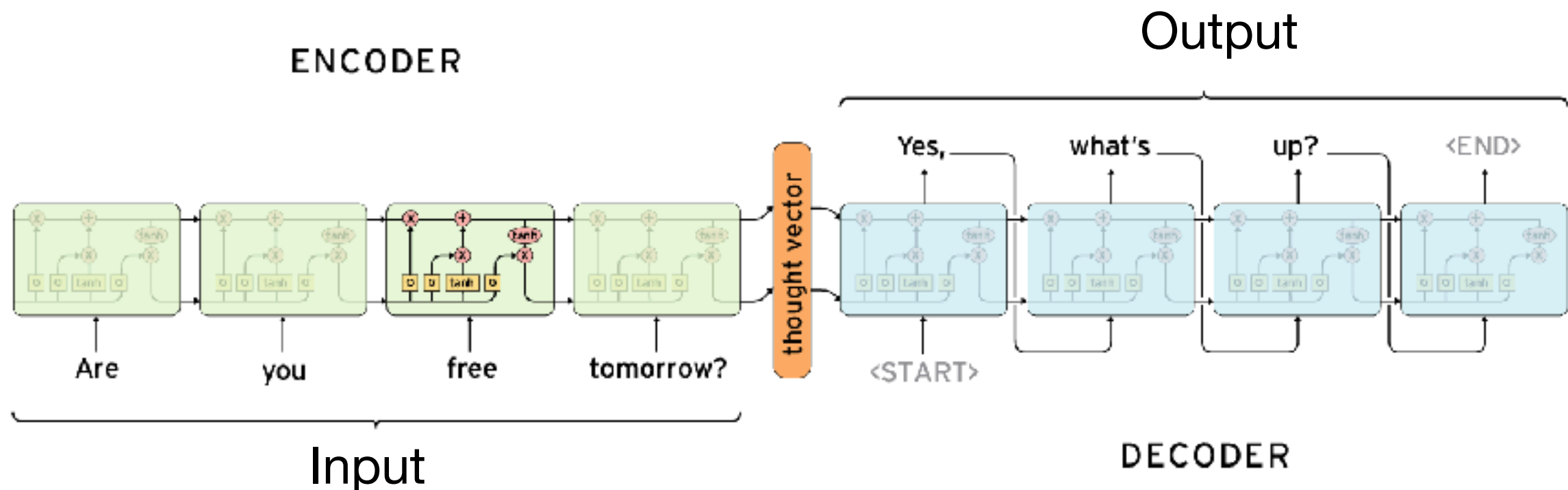
**OUTPUT:** *I am good. Thanks for asking.*

**INPUT:** *You're asking me out. That's so cute. What's your name again?*

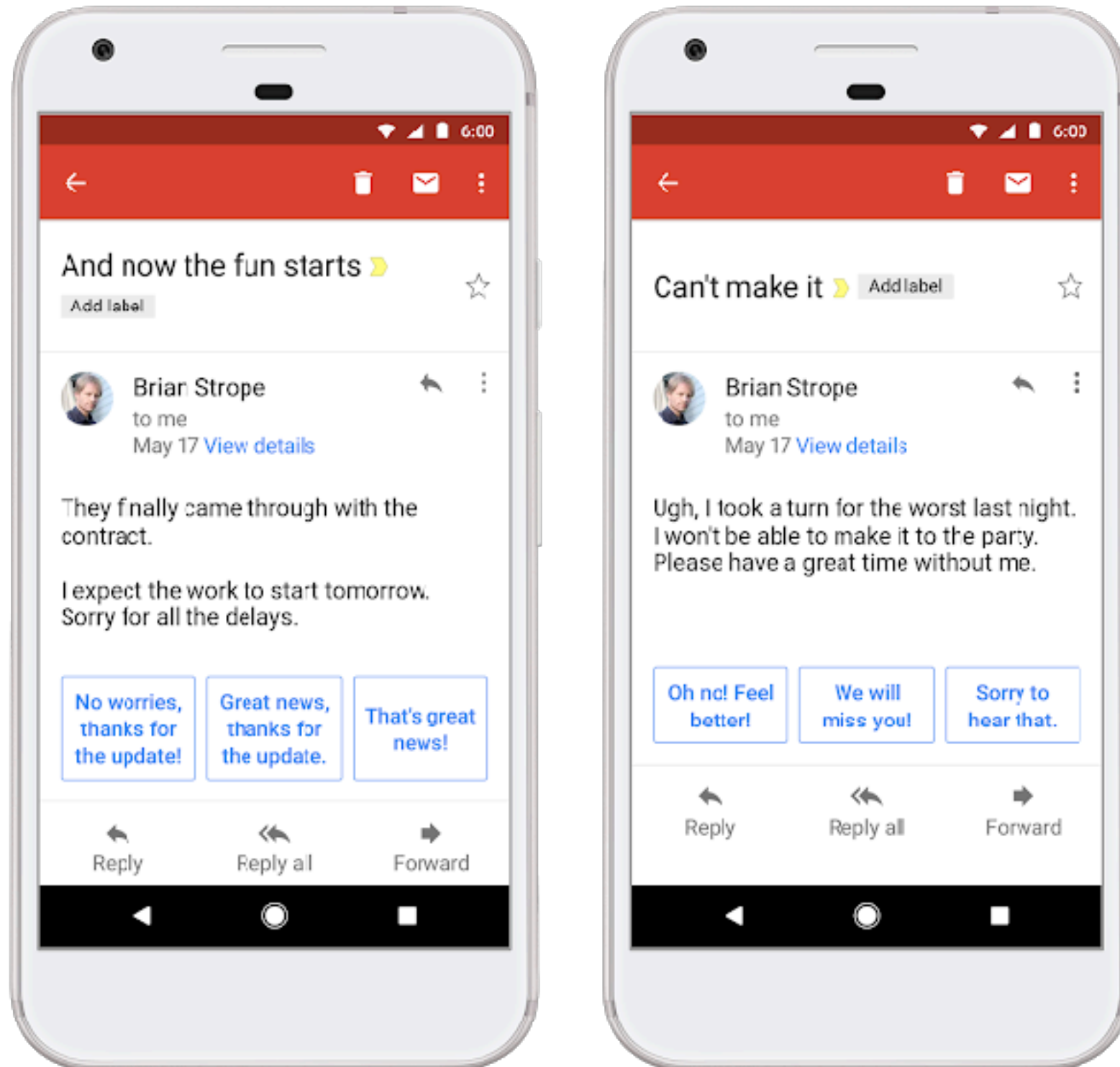
**OUTPUT:** *Forget it.*

**INPUT:** *No, no, it's my fault — we didn't have a proper introduction*

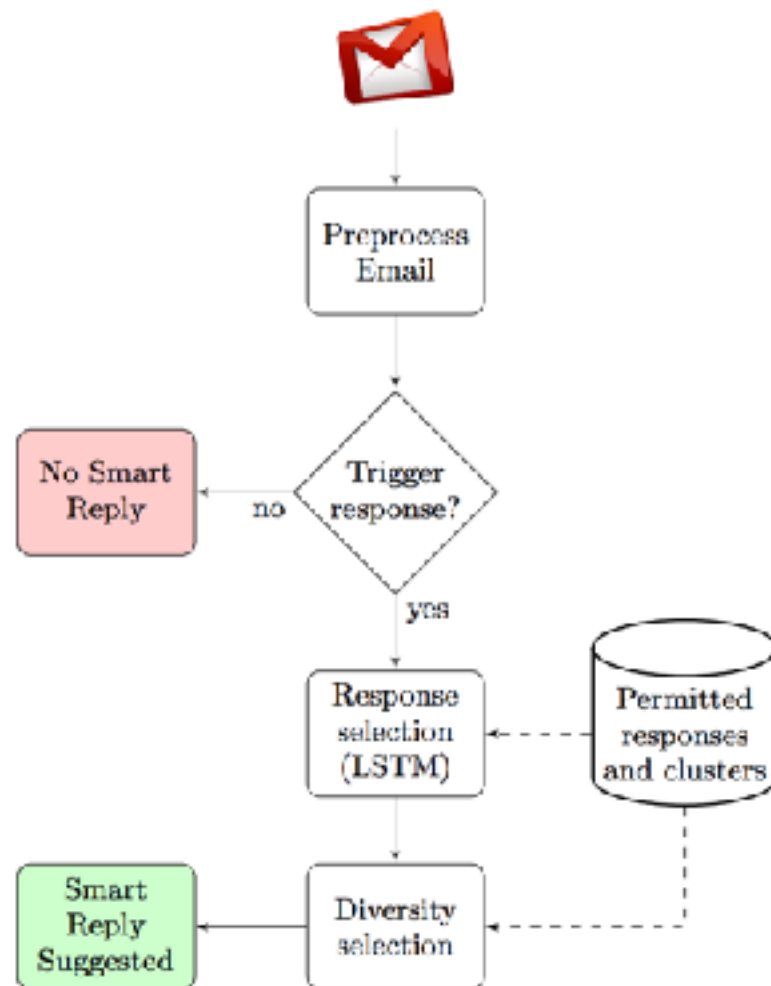
**OUTPUT:** *Cameron.*



# Auto-Reply



# Auto-Reply



Query	Top generated responses
Hi, I thought it would be great for us to sit down and chat. I am free Tuesday and Wenesday. Can you do either of those days?	I can do Tuesday. I can do Wednesday. How about Tuesday? I can do Tuesday! I can do Tuesday. What time works for you? I can do Wednesday! I can do Tuesday or Wednesday. How about Wednesday? I can do Wednesday. What time works for you? I can do either.
Thanks!	
-Alice	

# Summary

- RNNs/LSTMs are powerful tools
- Diverse applications
- What NEW problems will you solve?



# Online References

- <https://distill.pub/2017/ctc/>

# References

- Graves et al., Connectionist temporal classification: labelling unsegmented sequence data with recurrent neural networks, ICML 06

**Thank You**

**Questions?**