



Natural Language Processing with Small Feed-Forward Networks

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Goal: Small and Fast (on CPU/mobile)

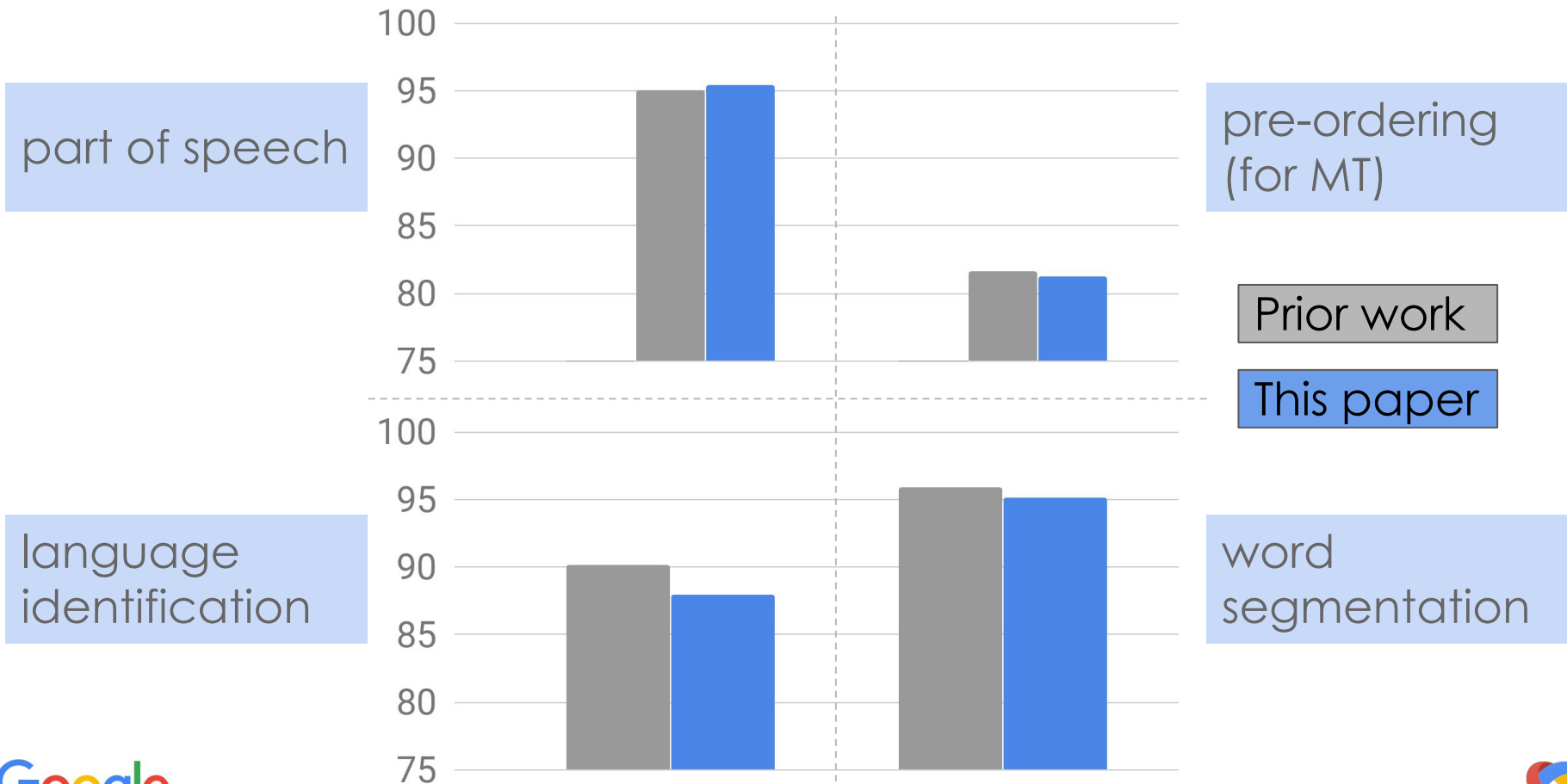
Deep recurrent models: can have 100s of millions (or billions) of parameters

Recent work on smaller recurrent models: Kim and Rush, 2016; Sharp Models on Dull Hardware, Devlin, EMNLP 2017 10's to 100 tokens/second

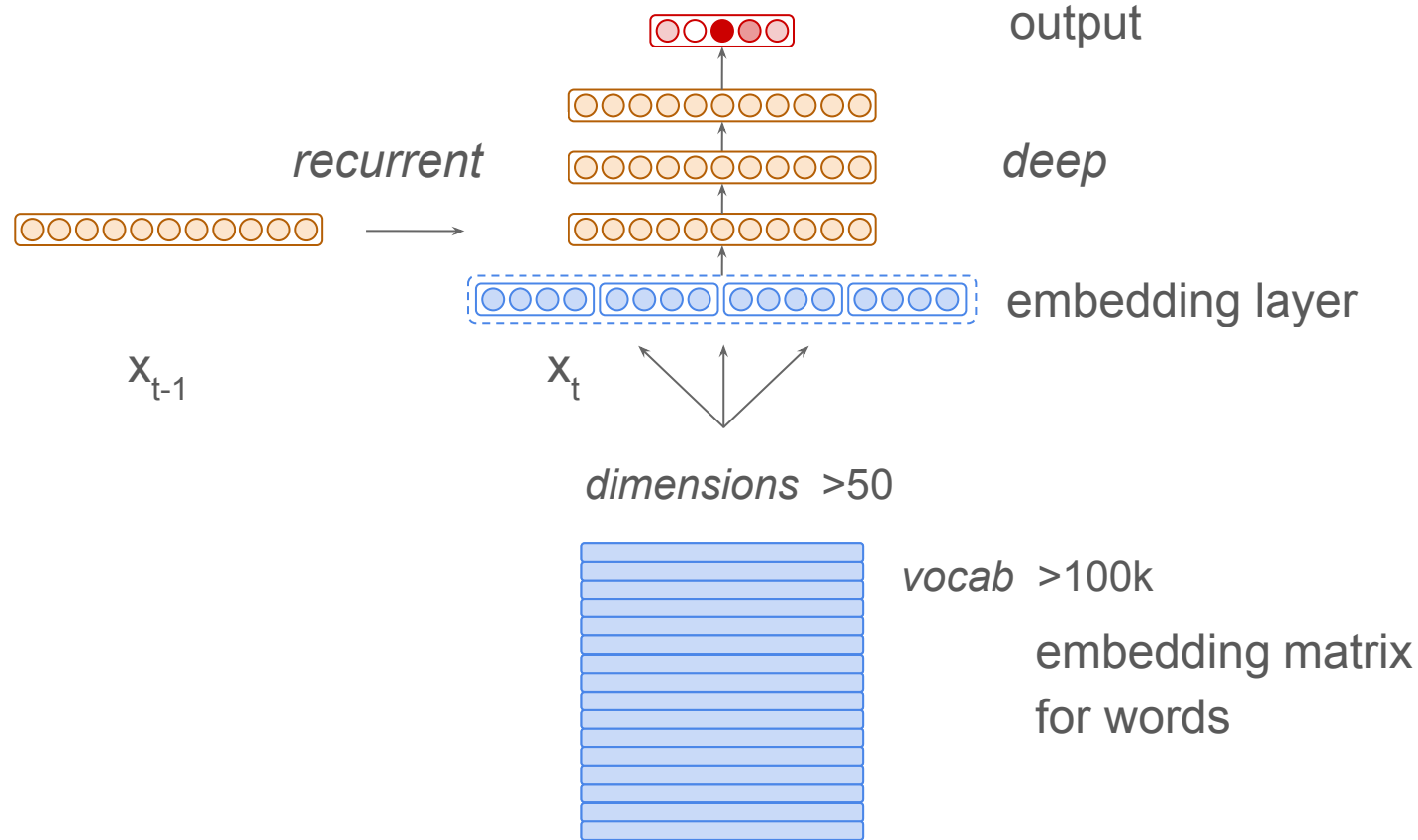
For variety of NLP tasks, can get order of magnitude speedup over LSTMs

Memory	≤ 2 MB
Speed	7k – 46k tokens/second
Trained	in a few hours

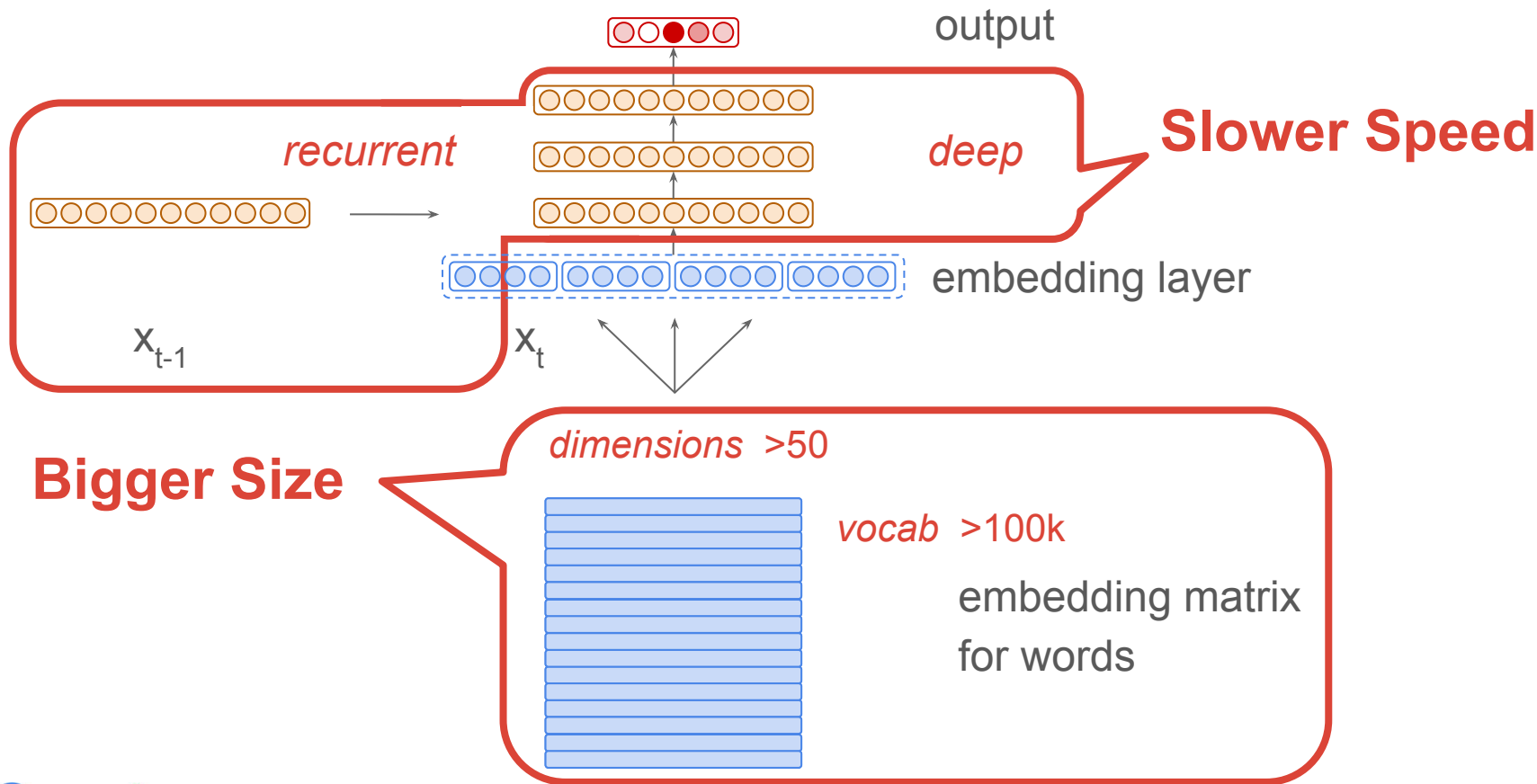
...With Near State-of-the-Art Accuracies in 4 Tasks



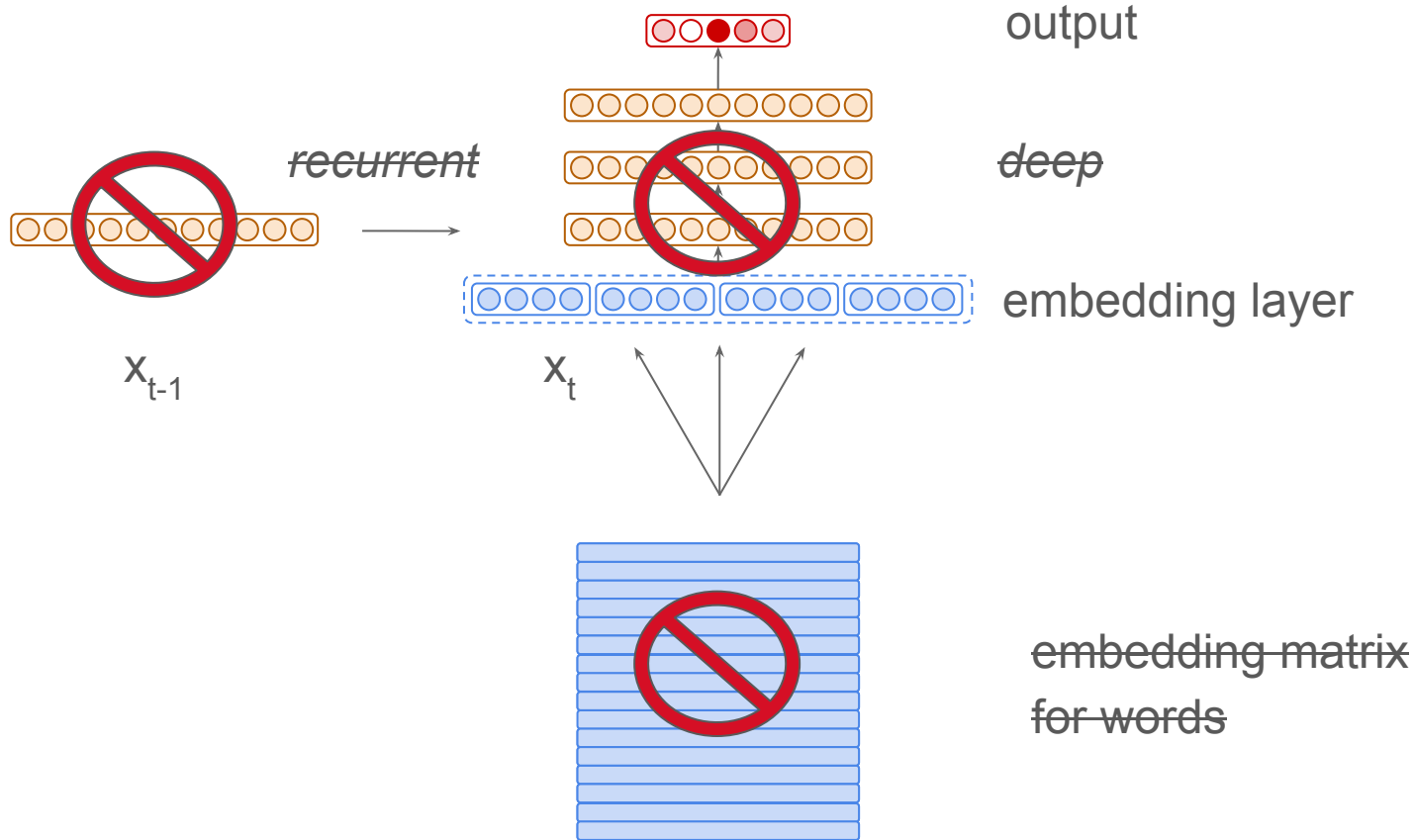
A Recurrent & Deep Model with Large Vocabulary



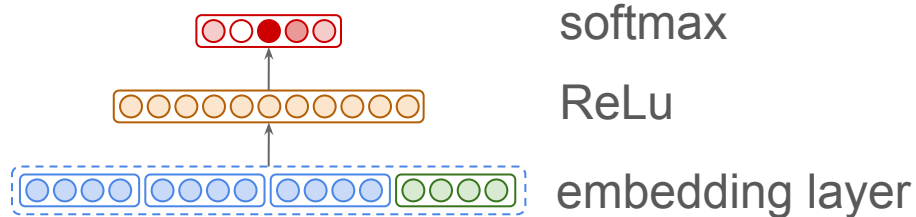
A Recurrent & Deep Model with Large Vocabulary



How Best to Allocate a Small Memory Budget?



What's Left? Small Feed-Forward Architecture



Goals



Accuracy

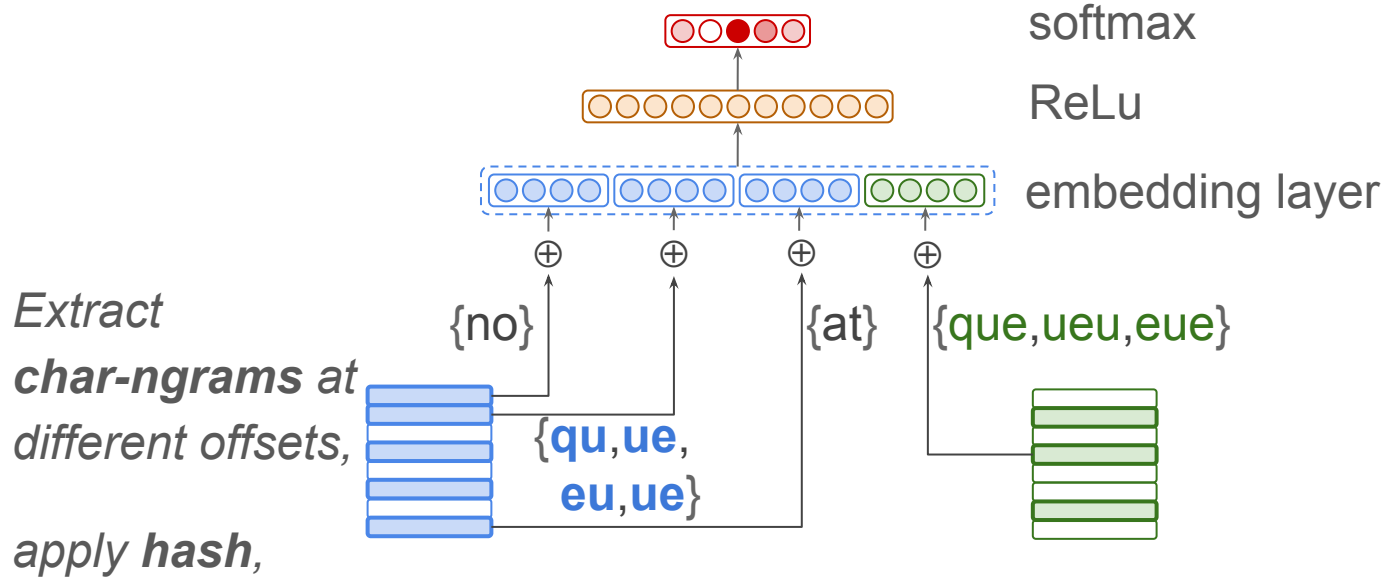
Word Clusters
Pipelines
Selected Features



Model Size

Hashed Character n-grams
Quantization

Input Representation: Hashed Character n-grams



aggregate
looked up
embeddings.

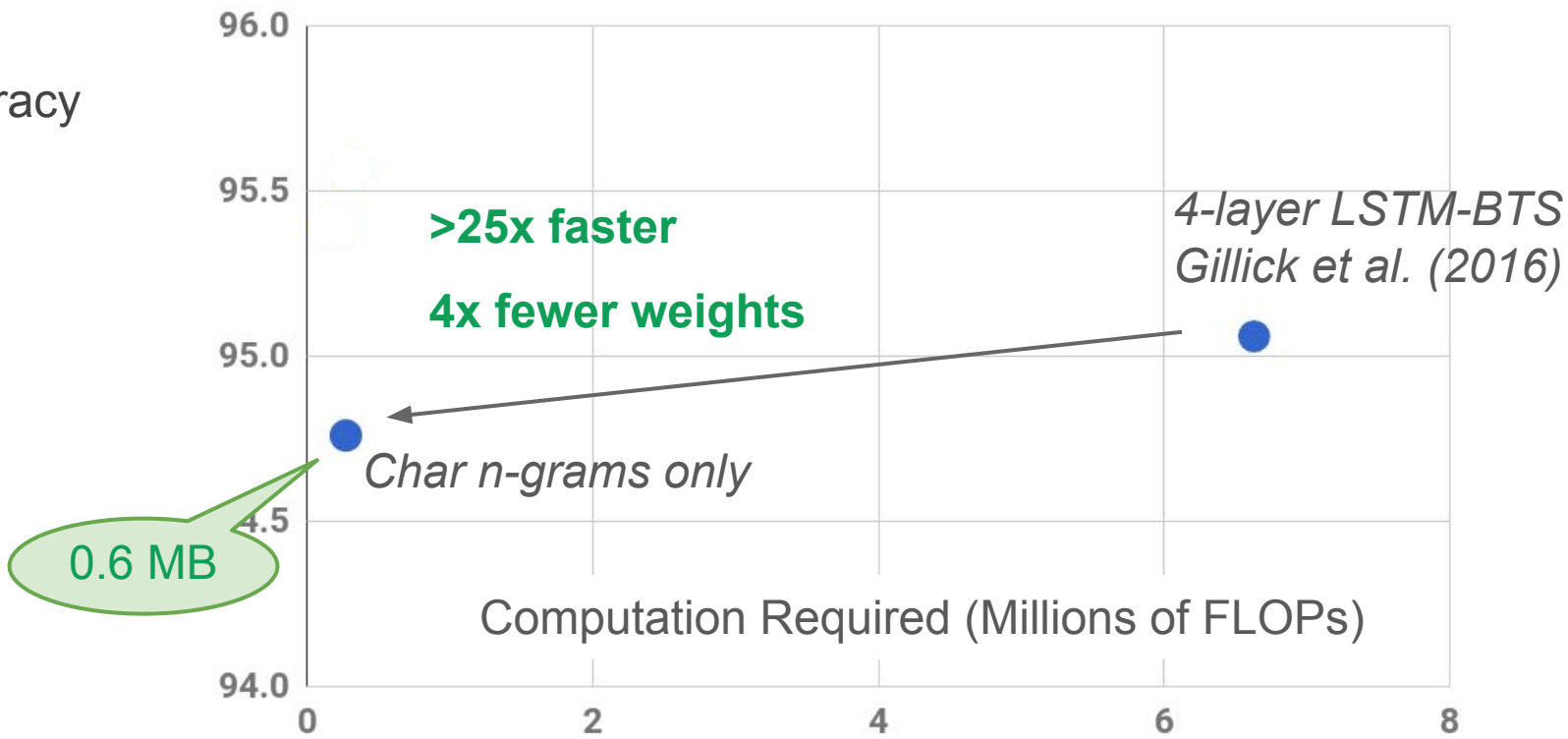
There was no queue at the ...



Case Study 1: POS Tagging

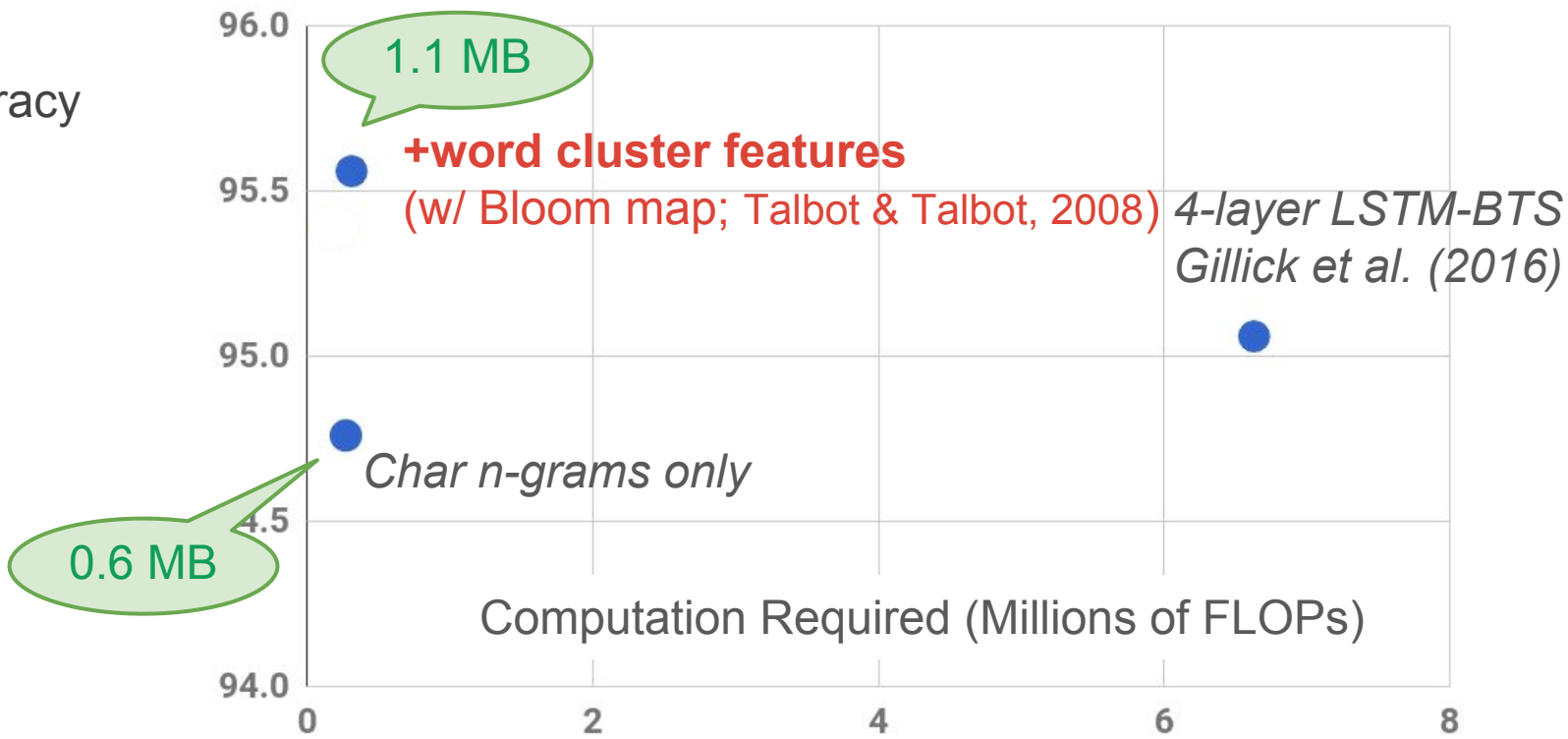
Vanilla Model: Less Resources, Little Less Accurate

POS
Accuracy

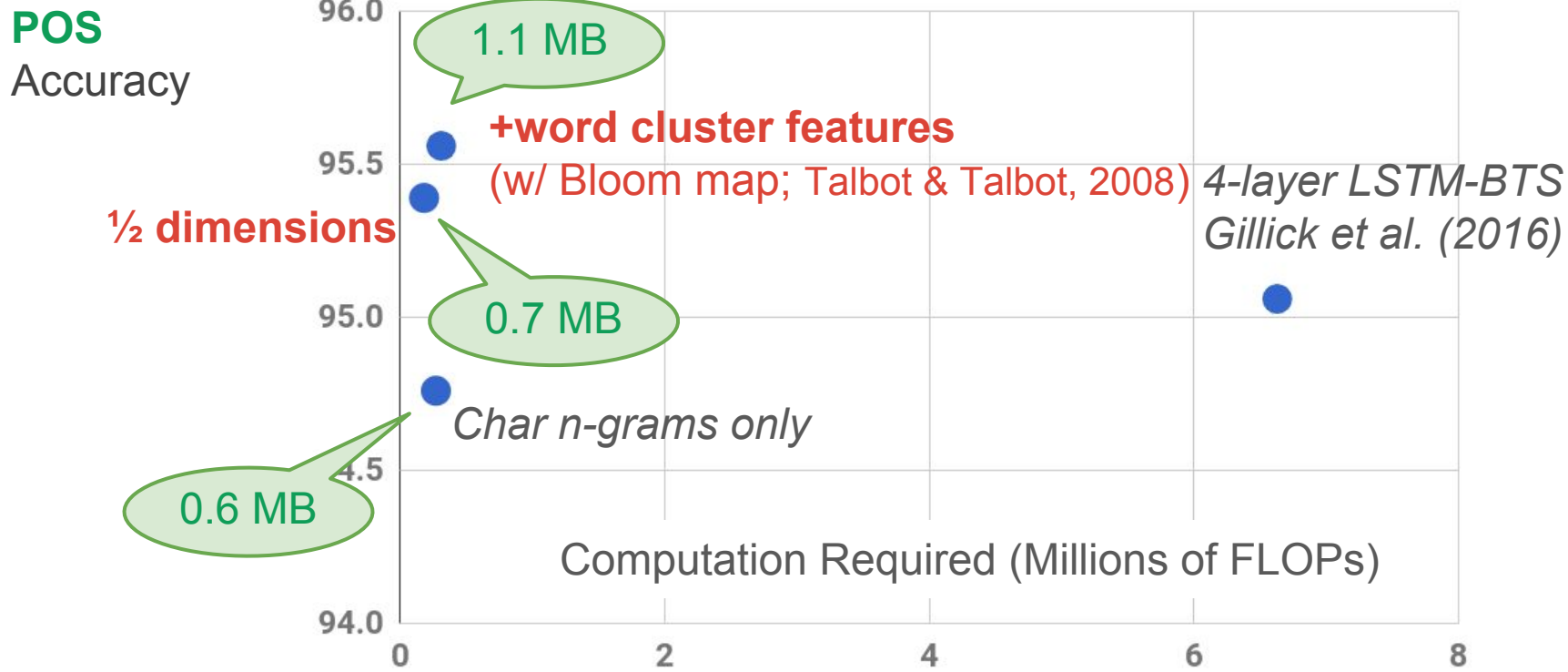


Accuracy Boost Adding Resource-backed Features

POS
Accuracy



Allows Reducing Embedding Dimensions Further





Case Study 2: Preordering for MT

Transition System for Structured Output

English → Japanese word ordering: I ate pizza → I pizza ate

Stack

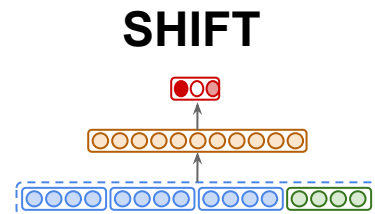
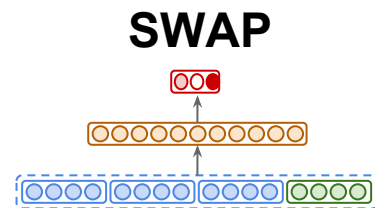
I ate pizza

Buffer



I pizza

ate



POS Tags as Intermediate Representation

Stack

I/PRP pizza/NN

PRP



NN



I ate pizza

I ate pizza

Buffer

ate/VBD

VBD

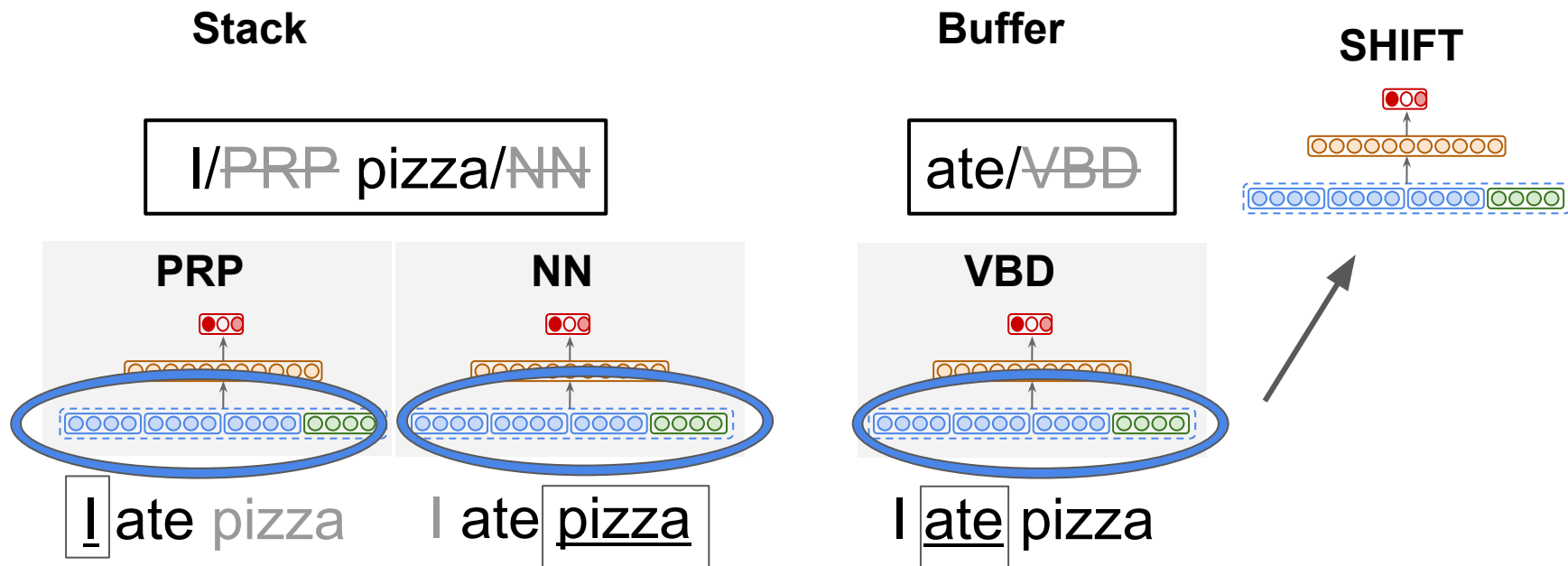


I ate pizza

SHIFT

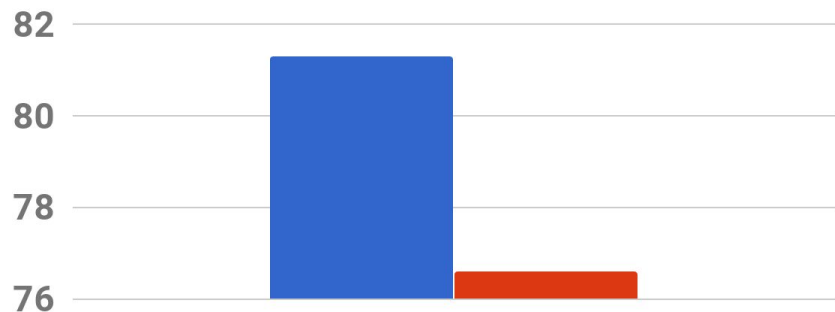


Or, “End-to-End Style” with Features from Tagger

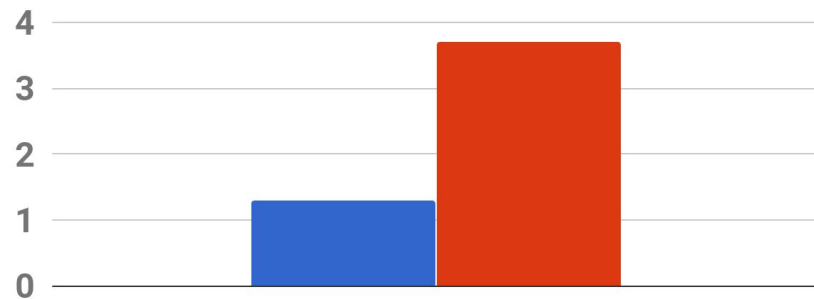


Pipeline: Higher Accuracy for Smaller Size

Reordering Score



Model Size (MB)



- Pipeline: POS tags → Preordering
- End-to-end: Preordering+Tagger features



Case Study 3: Language Identification

LangID: Post-hoc Quantization to Reduce Space

Baldwin & Lui (2010)

.870 - .902

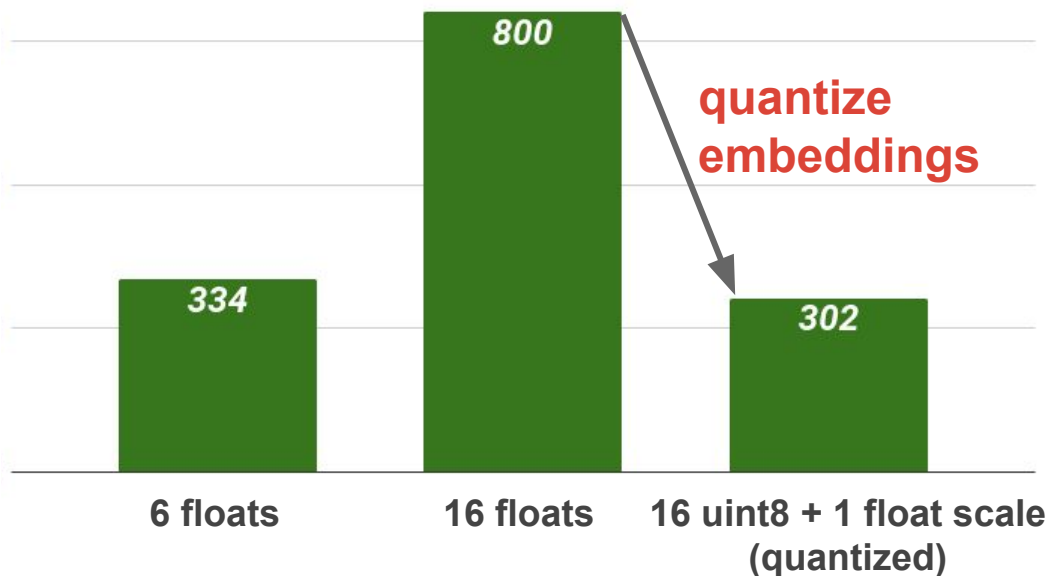
F1:

.873

.880

.880

Model size
(KB)



6 floats

16 floats

16 uint8 + 1 float scale
(quantized)

6 dimensions

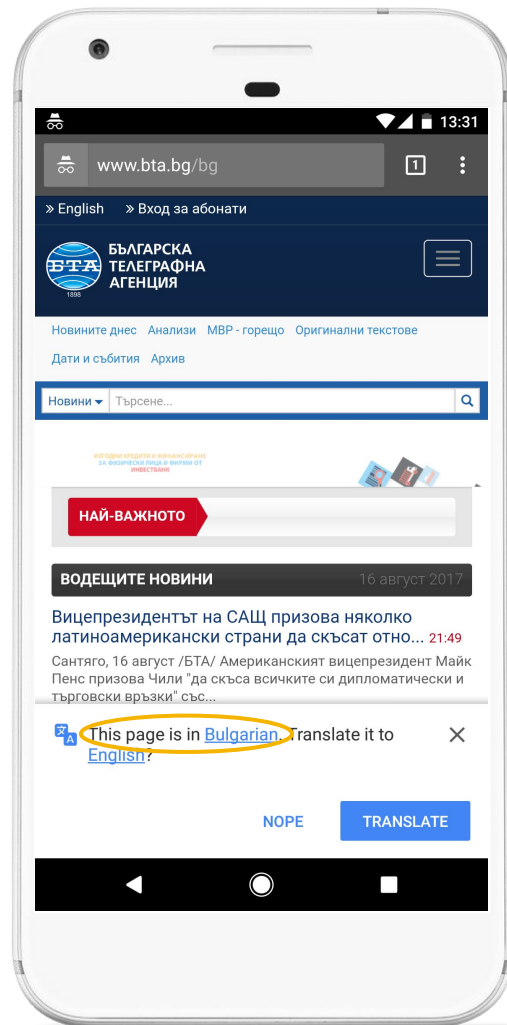
16 dimensions

That LangID model is essentially...

Compact Language Detector v3 (CLD3)

- ✓ runs inside all Google Chrome browsers
- ✓ code: github.com/google/CLD3

Actual screenshot from 16 Aug 2017



Conclusion

Small (≤ 2 MB) & fast (7k - 46k tokens/second) models with high accuracy in multiple tasks

Explicit intermediate representations & engineered features bring big accuracy gains in low-memory setting

Simple techniques \rightarrow easy to include in standard practice