Categorical Feature Compression via Submodular Optimization

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Pacific Ballroom #142

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Why Vocabulary Compression?

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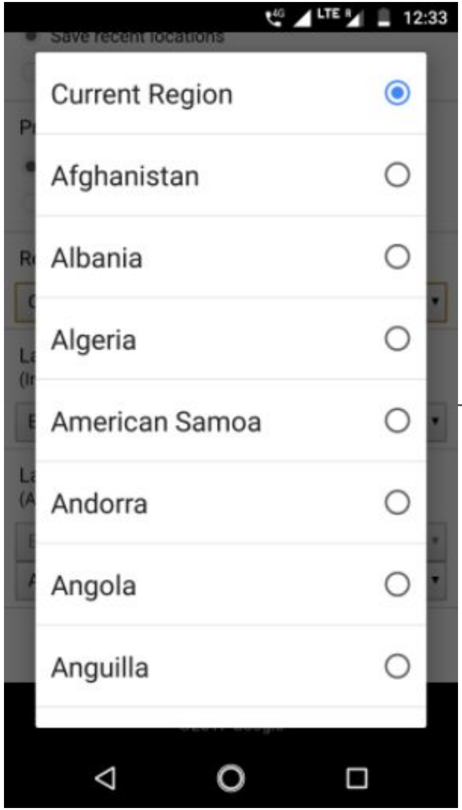
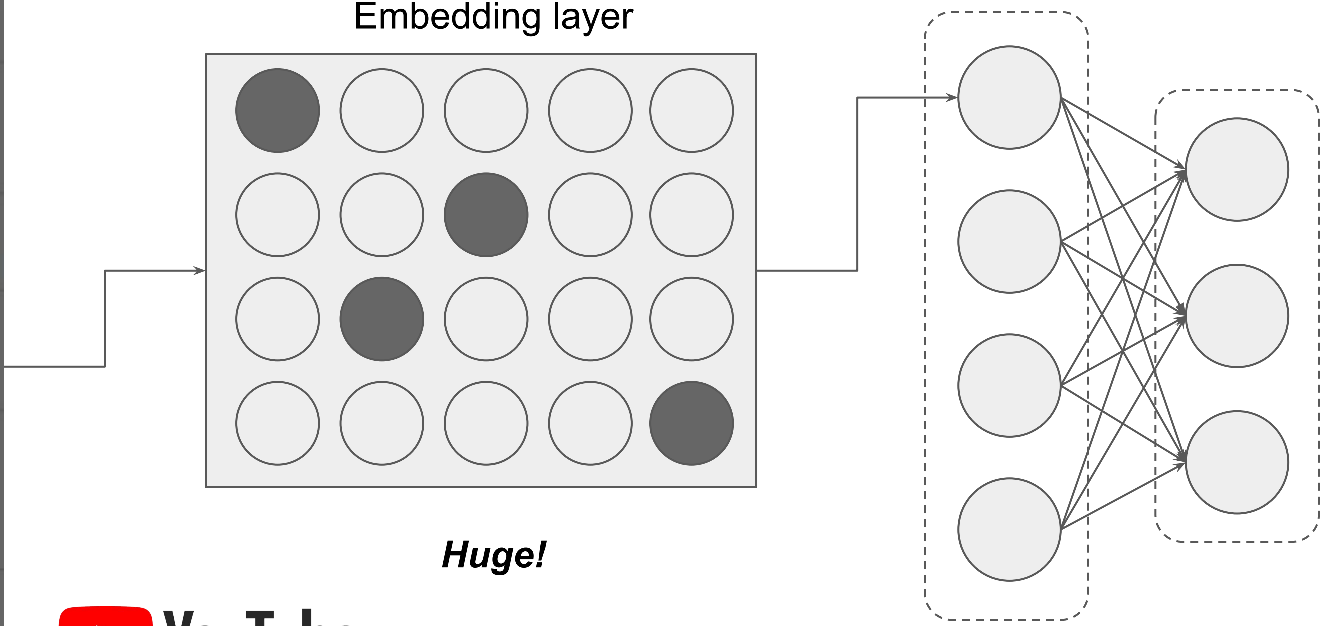


Embedding layer



Huge!

Video ID: ~7 billion values
99.9% of neural net

How to Compress Vocabulary?

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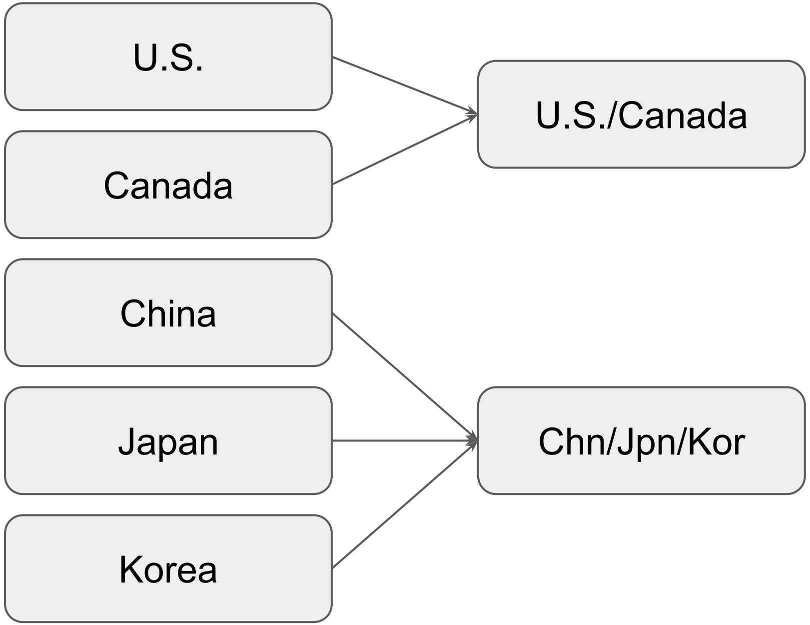

Group similar feature values into one.

Good compression preserves ***most information of labels***.

Supervised

Problem Formulation

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User ID	Featur e	Compressed feature	Favorite fruit (label)
#1843	China	China/Japan/Korea	
#429	Japan	China/Japan/Korea	
...			
#9077	Brazil	Brazil/Argentina	

Random variable X ∈ {Afghanistan, Albania, …, Zimbabwe}

Compressed feature f(X) ∈ {China/Japan/Korea, Brazil/Argentina, U.S./Canada}

Random variable C ∈ {pear, apple, …, mango}

Max I(f(X); C)

s.t. f(X) can take at most *m* values

Our Results

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Max I(f(X); C)

s.t. f(X) can take at most *m* values

There is a ***quasi-linear*** (O(n log n)) algorithm that achieves ***63%*** f(OPT) if label is ***binary***.

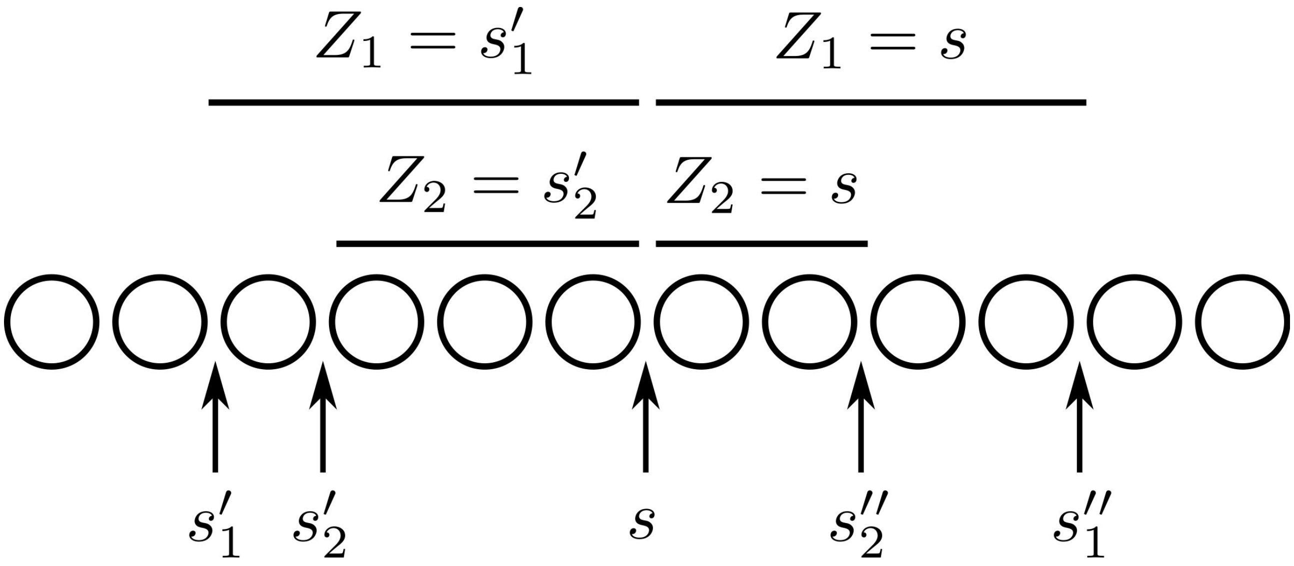
- Design a new submodular function after re-parametrization

There is a ***log(n)***-round distributed algorithm that achieves ***63%*** f(OPT) with ***O(n/k)*** space per machine.

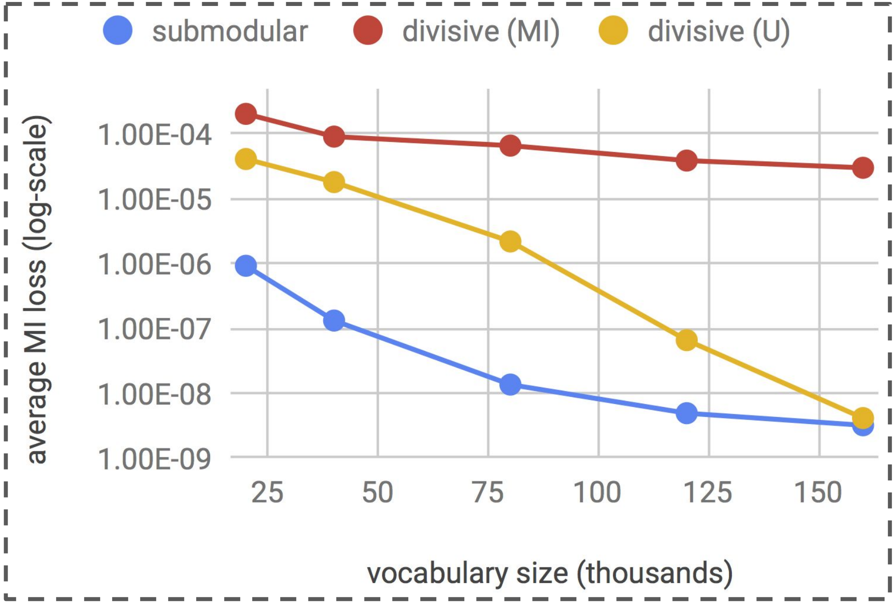
- *k* is # of machines

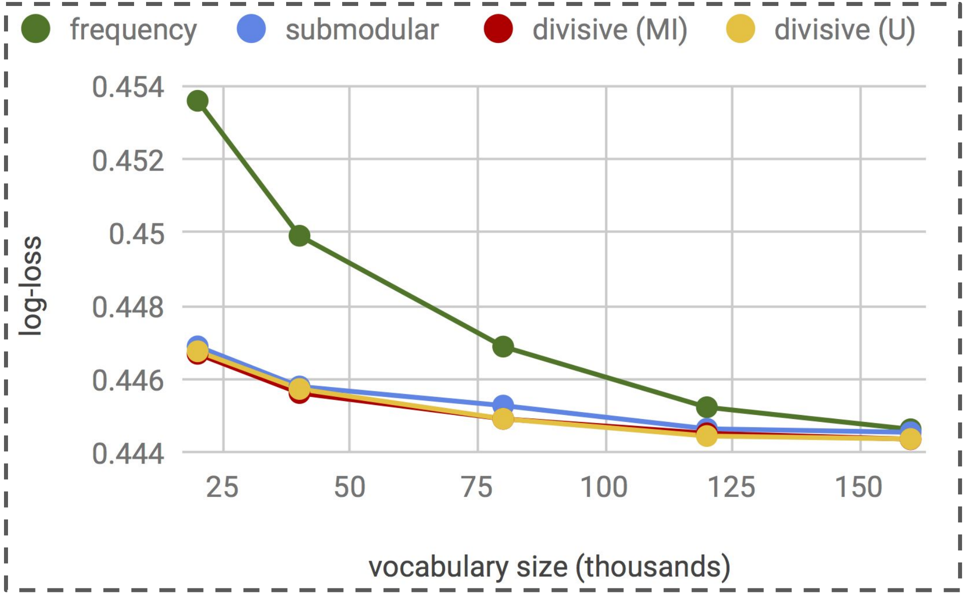
Reparametrization for Submodularity

- Sort feature values ***x*** according to ***P(X=x|C=0)***.
- A problem of placing separators
- ***I(f(X); C)*** is a function of the set of separators.



Experiment Results





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See you this evening