



Deep Learning at Twitter's Scale

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- 2 Workflow/Platform**
- 3 Modeling and Optimizations**
- 4 Additional Performance Gains**
- 5 GPU**



Background

- **Challenges: Characteristics of Platform**
- **Data Shift**



Challenges

VERY

DATA

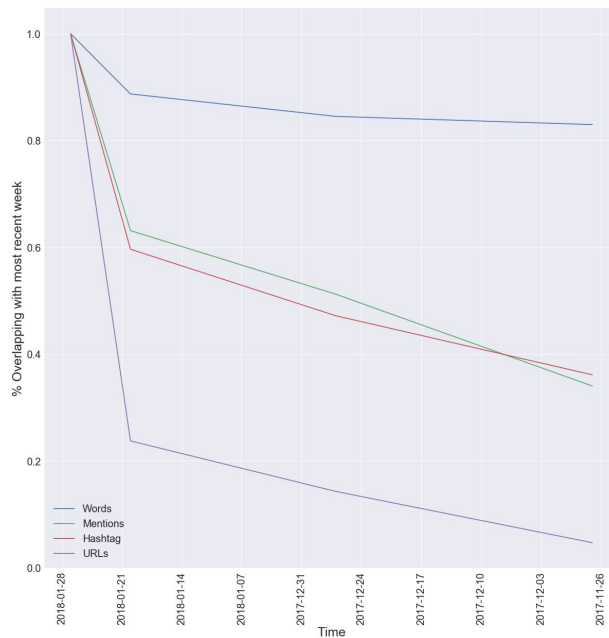
SPARSE



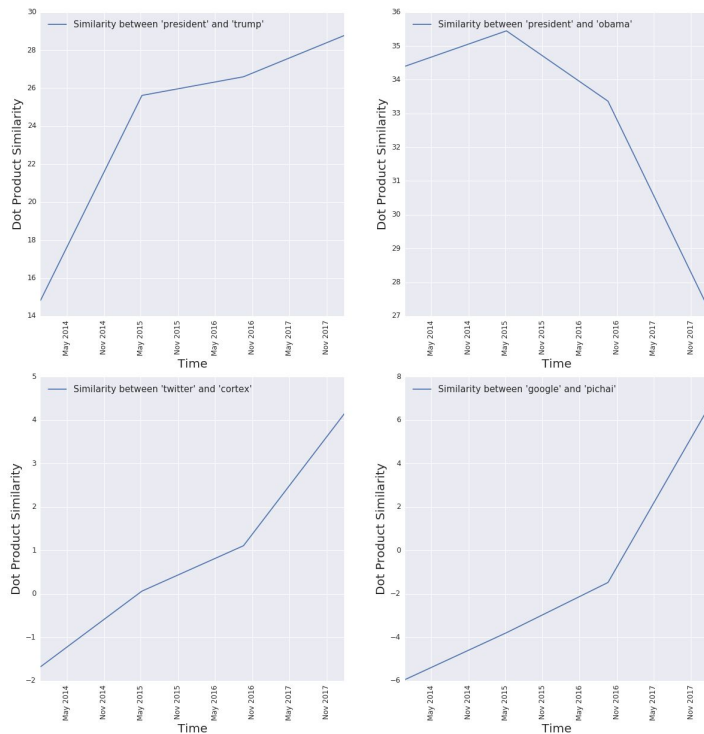
Challenges



Data Shift



Data Shift

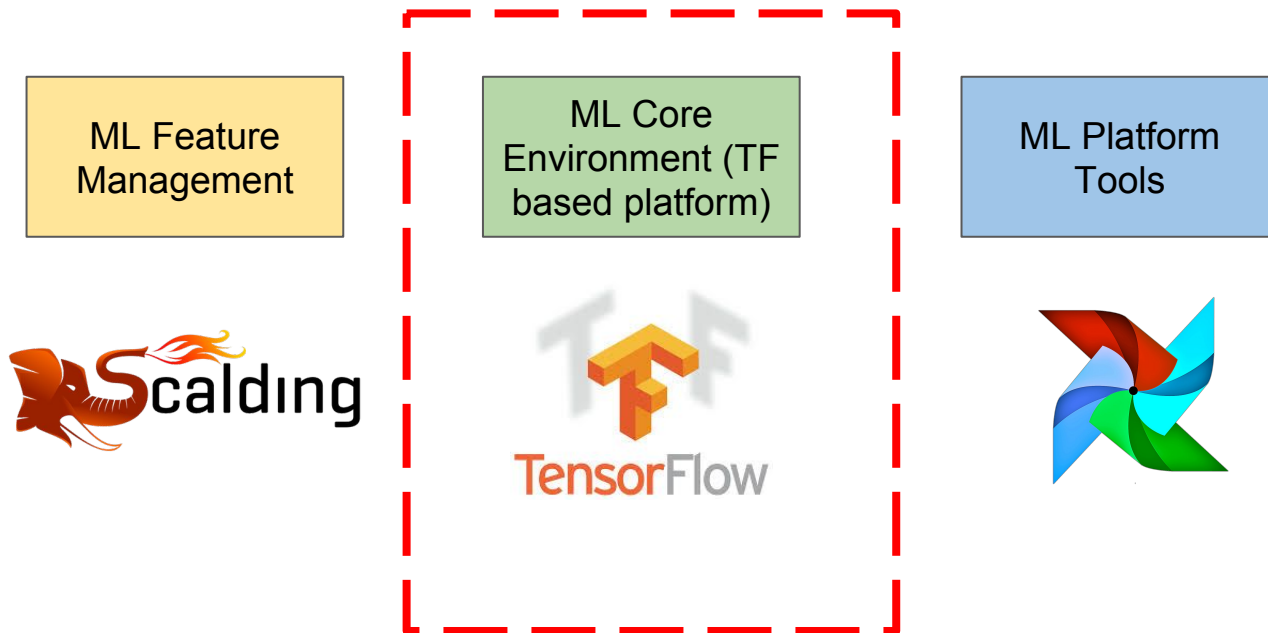


Machine Learning at the Company

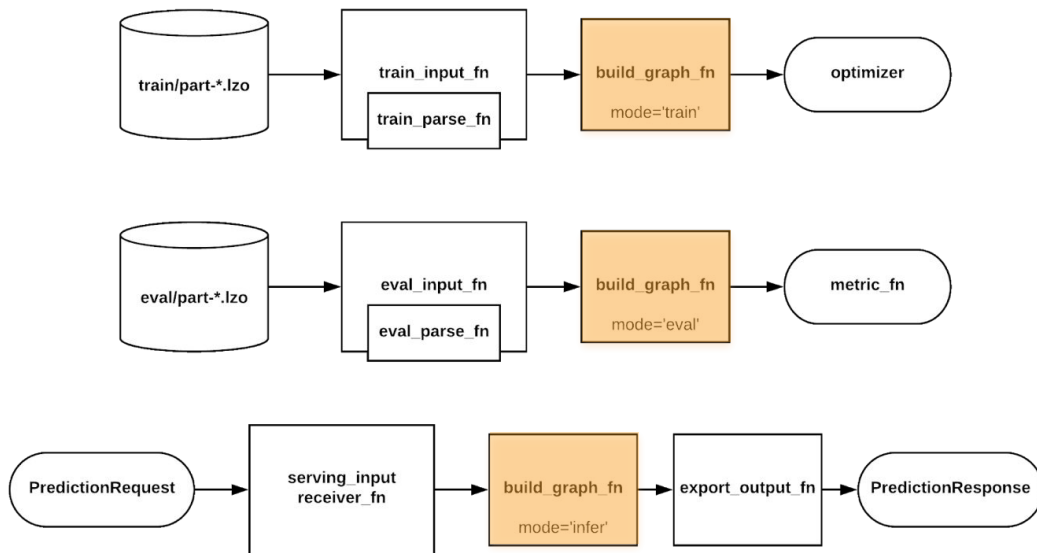
- **Environment**
- **Modeling: some use cases**



Environment: ML Platforms



Environment: ML Training



Environment: Priorities

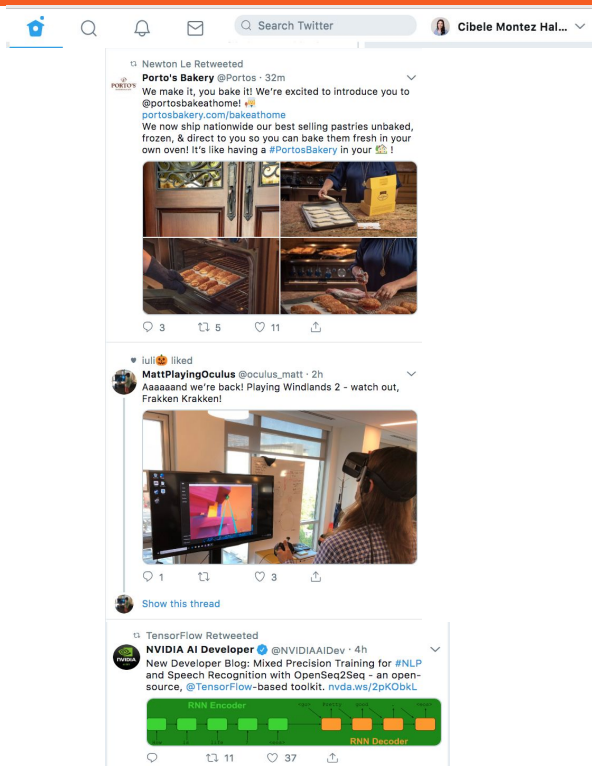
- Feature Addition → Scalable data
- Data Addition → Scalable data
- **Training → Fast, robust training engine**
- **Deployment → Seamless and tested ML services**
- A/B test → Good AB test environment



Modeling Use Cases: Timelines



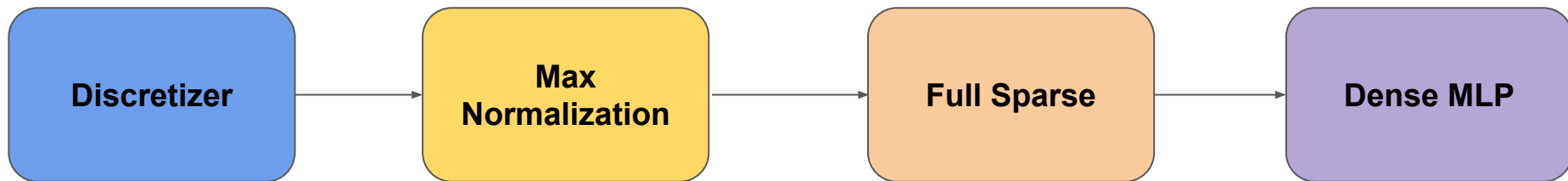
Modeling Use Cases: Timelines



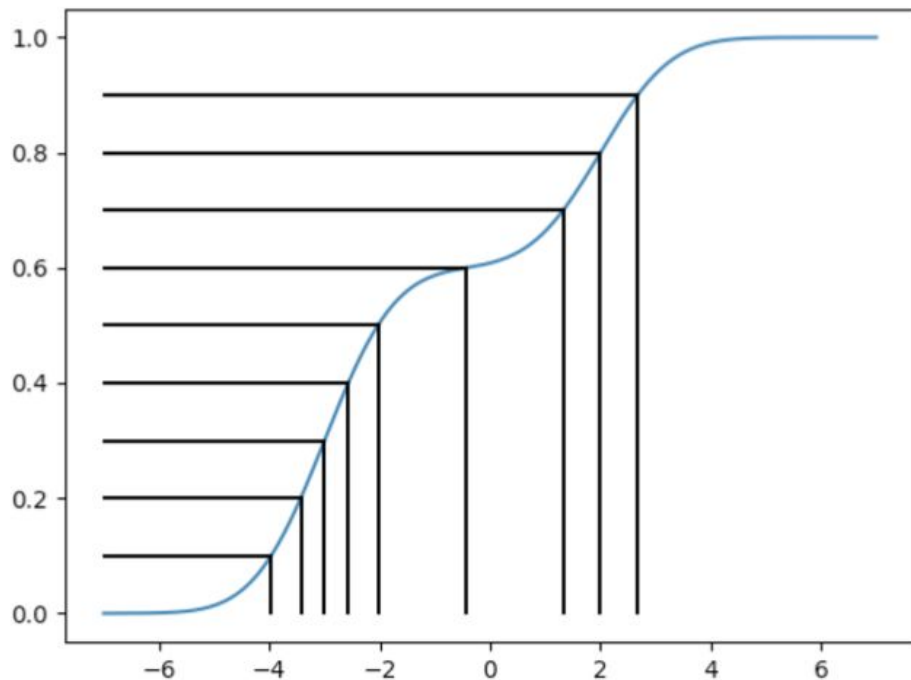
Modeling: Modeling and Optimizations with TensorFlow



Modeling



Modeling: Discretizer



Sparse Linear Layer: Online Normalization

- Example:

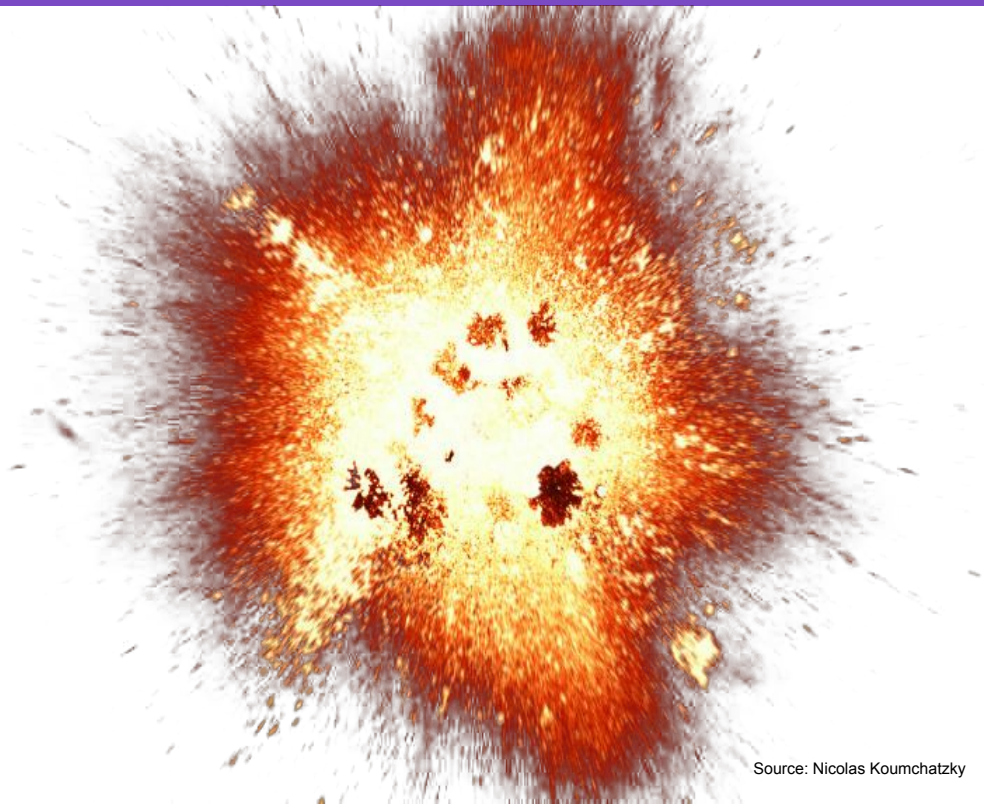
Input: input_feature (value == 1M)
⇒ weight_gradient == 1M
⇒ update = 1M * learning_rate
⇒ ?



Sparse Linear Layer: Online Normalization

- Example:

Input: input_feature (value == 1M)
⇒ weight_gradient == 1M
⇒ update = 1M * learning_rate
⇒



Sparse Linear Layer: Online Normalization

- Normalization of input values

$$\text{norm}(V_i) == \boxed{V_i / \max(|V_i|)} + \boxed{b_i}$$

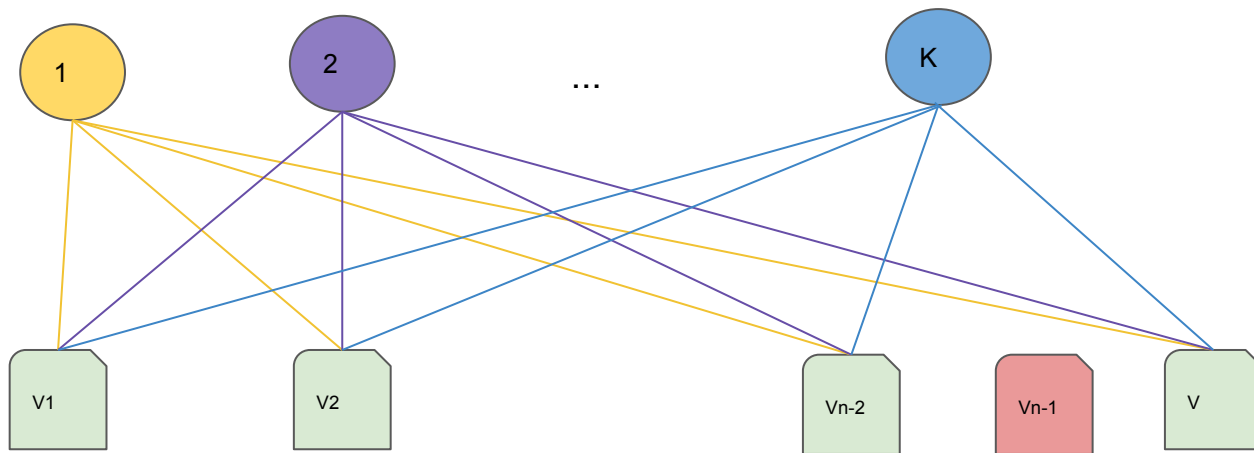
Belongs to $[-1, 1]$

Trainable per-feature bias:
discriminate absence and presence
of features



Modeling: Sparse Linear Layer

$$N_j = F(\sum W_{i,j} * \text{norm}(V_i) + B_j)$$



Sparse Linear Layer: Batching Data Records

`__init__`

```
__init__(  
    indices,  
    values,  
    dense_shape  
)
```

Indices[:,0] = sample indices
Indices[:,1] = feature keys

Creates a `SparseTensor`.

Args:

- `indices`: A 2-D int64 tensor of shape `[N, ndims]`.
- `values`: A 1-D tensor of any type and shape `[N]`.
- `dense_shape`: A 1-D int64 tensor of shape `[ndims]`.



Sparse Linear Layer: First Approach

tf.sparse_tensor_dense_matmul



```
tf.sparse_tensor_dense_matmul(  
    sp_a,  
    b,  
    adjoint_a=False,  
    adjoint_b=False,  
    name=None  
)
```

Defined in [tensorflow/python/ops/sparse_ops.py](#).

See the guide: [Sparse Tensors > Math Operations](#)

Multiply SparseTensor (of rank 2) "A" by dense matrix "B".

No validity checking is performed on the indices of `A`. However, the following input format is recommended for optimal behavior:



Sparse Linear Layer: Final Approach

tf.nn.embedding_lookup_sparse

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```
tf.nn.embedding_lookup_sparse(  
    params,  
    sp_ids,  
    sp_weights,  
    partition_strategy='mod',  
    name=None,  
    combiner=None,  
    max_norm=None  
)
```

Defined in [tensorflow/python/ops/embedding_ops.py](#).

See the guide: [Neural Network > Embeddings](#)

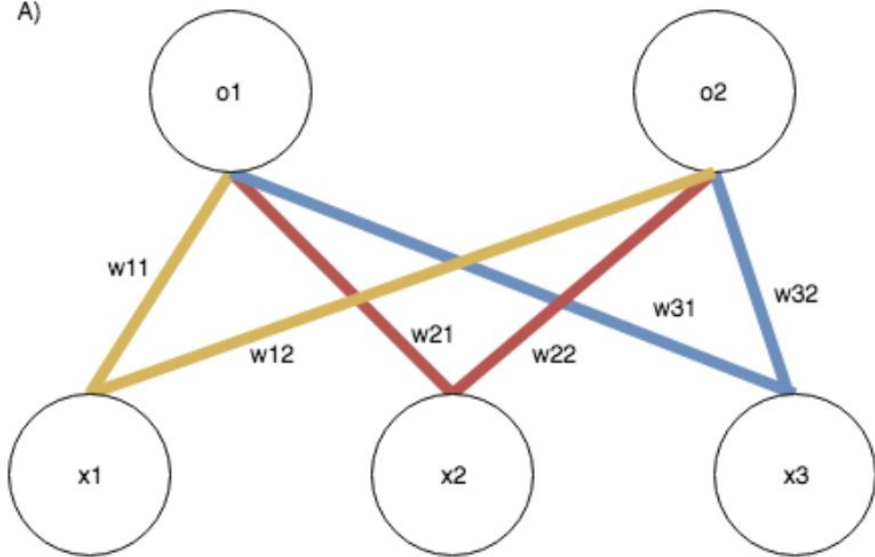
Computes embeddings for the given ids and weights.

This op assumes that there is at least one id for each row in the dense tensor represented by `sp_ids` (i.e. there are no rows with empty features), and that all the indices of `sp_ids` are in canonical row-major order.



Sparse Linear Layer: Variable Partitioning

A)



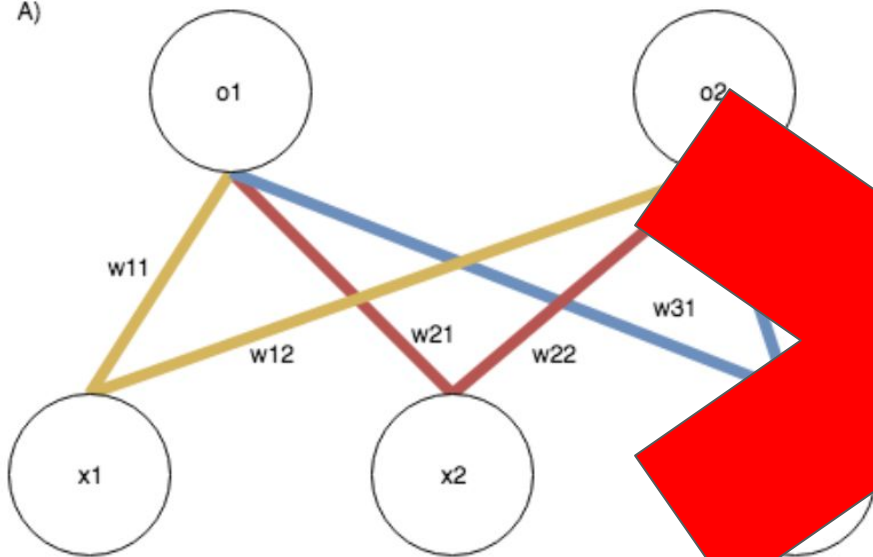
1. Shard 1 computes: $p_{11} = x_1 \times w_{11}, p_{12} = x_1 \times w_{12}$
2. Shard 2 computes: $p_{21} = x_2 \times w_{21}, p_{22} = x_2 \times w_{22}$
3. Shard 3 computes: $p_{31} = x_3 \times w_{31}, p_{32} = x_3 \times w_{32}$

output: $[p_{11} + p_{21} + p_{31}, p_{12} + p_{22} + p_{32}]$



Sparse Linear Layer: Variable Partitioning

A)



1. Shard 1 computes: $p_{11} = x_1 \times w_{11}, p_{12} = x_1 \times w_{12}$

2. Shard 2 computes: $p_{21} = x_2 \times w_{21}, p_{22} = x_2 \times w_{22}$

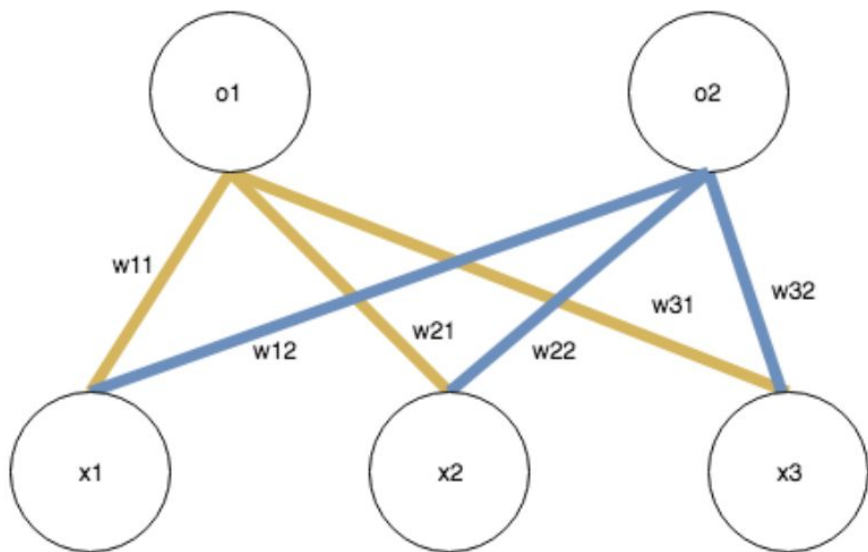
3. Shard 3 computes: $p_{31} = x_3 \times w_{31}, p_{32} = x_3 \times w_{32}$

$[p_{11} + p_{21} + p_{31}, p_{12} + p_{22} + p_{32}]$



Sparse Linear Layer: Variable Partitioning

B)



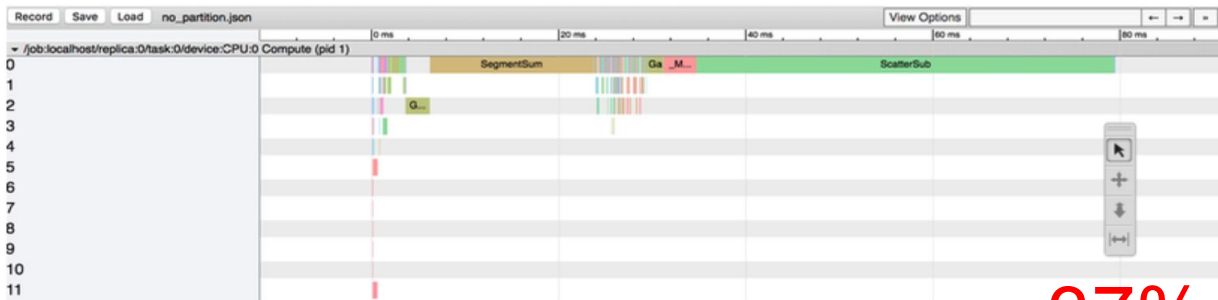
Shard 1 computes: $o_1 = x_1 \times w_{11} + x_2 \times w_{21} + x_3 \times w_{31}$

Shard 2 computes: $o_2 = x_1 \times w_{12} + x_2 \times w_{22} + x_3 \times w_{32}$

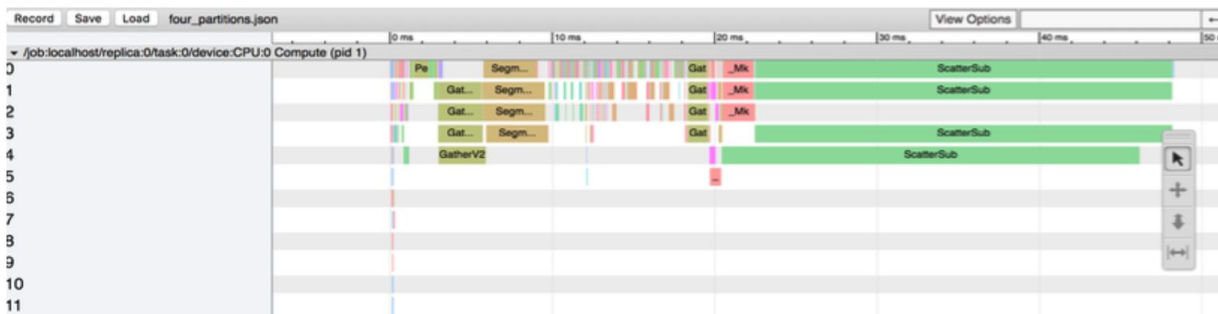
output: $[o_1, o_2]$



Sparse Linear Layer: Variable Partitioning: Profiling



~37% reduction

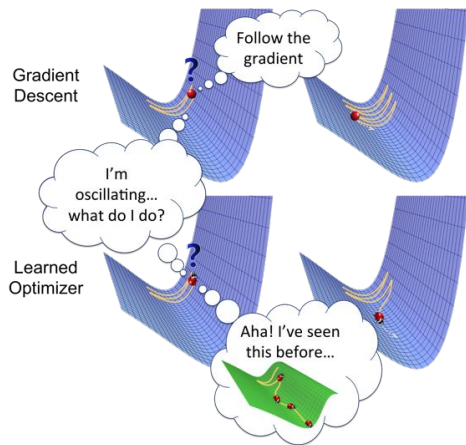


Sparse Linear Layer

- Optimizers
 - SGD
 - Lazy Adam

Adam:

“Velocity”
“Momentum”

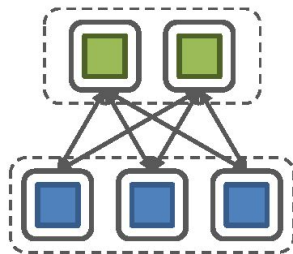
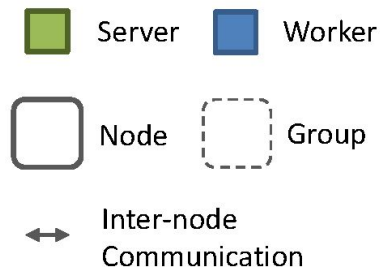


Additional Performance Gains

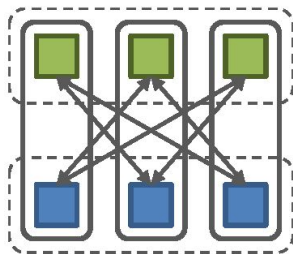


Hogwild

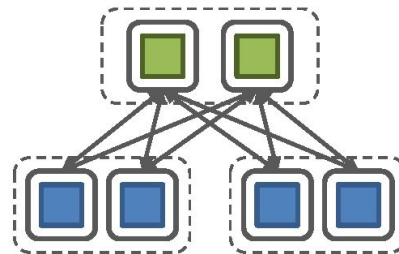
“Remove all thread locks from parallel SGD code.”



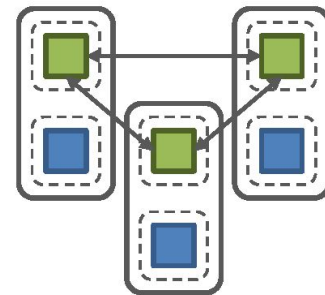
(a) Sandblaster.



(b) AllReduce.



(c) Downpour.



(d) Distributed Hogwild.

Each thread draws a random example i from the training data.

- Thread reads current state of θ .
- Thread updates $\theta \leftarrow (\theta - \alpha \nabla L(f_{\theta}(x_i), y_i))$.



Hogwild

tf.estimator.train_and_evaluate



```
tf.estimator.train_and_evaluate(  
    estimator,  
    train_spec,  
    eval_spec  
)
```



Defined in [tensorflow/python/estimator/training.py](#).

Train and evaluate the `estimator`.

This utility function trains, evaluates, and (optionally) exports the model by using the given `estimator`. All training related specification is held in `train_spec`, including training `input_fn` and training max steps, etc. All evaluation and export related specification is held in `eval_spec`, including evaluation `input_fn`, steps, etc.

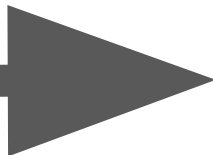


Custom Ops

tf.py_func

```
tf.py_func(  
    func,  
    inp,  
    Tout,  
    stateful=True,  
    name=None  
)
```

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```
#include "tensorflow/core/framework/op_kernel.h"  
  
using namespace tensorflow;  
  
class ZeroOutOp : public OpKernel {  
public:  
    explicit ZeroOutOp(OpKernelConstruction* context) : OpKernel(context) {}  
  
    void Compute(OpKernelContext* context) override {  
        // Grab the input tensor  
        const Tensor& input_tensor = context->input(0);  
        auto input = input_tensor.flat<int32>();  
  
        // Create an output tensor  
        Tensor* output_tensor = NULL;  
        OP_REQUIRES_OK(context, context->allocate_output(0, input_tensor.shape(),  
                                                         &output_tensor));  
        auto output_flat = output_tensor->flat<int32>();  
  
        // Set all but the first element of the output tensor to 0.  
        const int N = input.size();  
        for (int i = 1; i < N; i++) {  
            output_flat(i) = 0;  
        }  
  
        // Preserve the first input value if possible.  
        if (N > 0) output_flat(0) = input(0);  
    }  
};
```



GPU x CPU metrics



CPU/GPU Benchmarks: Remarks

- TensorFlow 1.10 compiled with MKL enabled
- Disabled MKL's multithreading by exporting OMP NUM THREADS=1
- Tweak parallelism: inter_op_parallelism_threads/intra_op_parallelism_threads



GPU Benchmarks

Batch Size/Model Optimization	CPU: Baseline (tf.sparse_tensor_dense_matmul)	CPU: After optimizations	GPU: Baseline (tf.sparse_tensor_dense_matmul)	GPU: After Optimizations
256	1024 samples/s	7372 samples/s	5504 samples/s	22528 samples/s
512	1638 samples/s	11264 samples/s	8448 samples/s	21504 samples/s
1024	2355 samples/s	13312 samples/s	10752 samples/s	22528 samples/s

GPU benchmarks were run with NVIDIA Tesla K80 Processors
CPU benchmarks were run with Intel Xenon Platinum 8180 Processors



Acknowledgements



- Andrew Bean
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Thank you!

Questions?

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