Machine Learning for CI

Kyra Wulffert
Matthew Treinish
Andrea Frittoli

Open Data Science Conference
London 2019

November 22, 2019

The Team

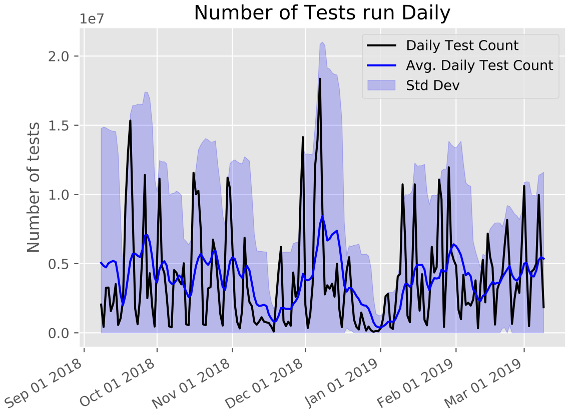
Kyra Wulffert
kwulffert@gmail.com

Matthew Treinish
mtreinish@kortar.org

Andrea Frittoli
andrea.frittoli@gmail.com

Data Sourcing

CI at Scale

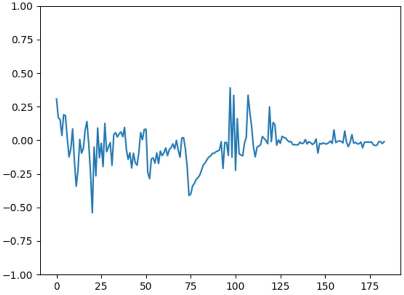


Source: subunit2sql-graph dailycount

- Continuous Integration
- Continuous Log Data
- Lots of data, little time
- Triaging failures?
- AI to the rescue!

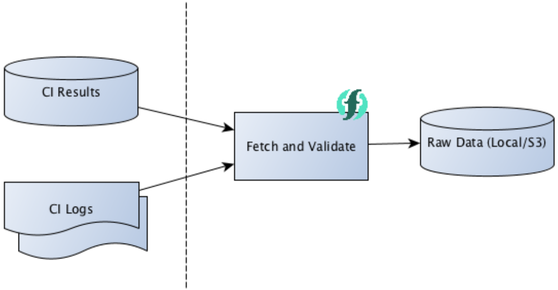
The OpenStack use case

- Integration testing in a VM
- System logs, application logs
- Dstat data
- Gate testing
- Not only OpenStack



Normalized system average load for different examples

Collecting data



Data caching diagram

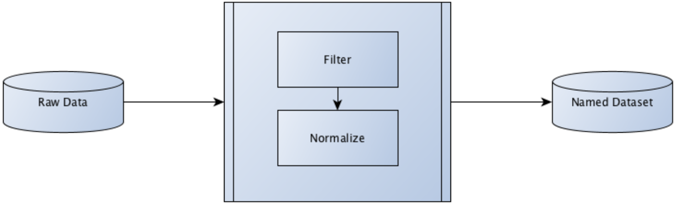
- Automation and repeatability
- Light-weight data validation
- Object storage for data
- Periodic Action on OpenWhisk

Data Preparation

Experiment Workflow

- **Visualize data**
- **Define a dataset**
- Define an experiment
- Run the training
- Collect results

```
# Build an s3 backed dataset
ciml-build-dataset --dataset cpu-load-1min-dataset \
  --build-name tempest-full \
  --slicer :2000 \
  --sample-interval 10min \
  --features-regex "(usr|1min)" \
  --class-label status \
  --tdt-split 7 0 3 \
  --data-path s3://cimlrawdata \
  --target-data-path s3://cimldatasets
```



Dataset preparation diagram

Data Selection

- What is dstat data?
- Experiment reproducibility
- Dataset selection
  - Dstat feature selection
  - Data resolution (down-sampling)

Sample of dstat data

time	usr	used	writ	1m
16/02/2019 21:44:52	6.1	$7.36 \cdot 10^8$	$5.78 \cdot 10^6$	0.97
16/02/2019 21:44:53	7.45	$7.43 \cdot 10^8$	$3.6 \cdot 10^5$	0.97
16/02/2019 21:44:54	4.27	$7.31 \cdot 10^8$	$4.01 \cdot 10^5$	0.97
16/02/2019 21:44:55	1	$7.43 \cdot 10^8$	4,096	0.97
16/02/2019 21:44:56	0.5	$7.44 \cdot 10^8$	$1.5 \cdot 10^7$	0.97
16/02/2019 21:44:57	1.75	$7.31 \cdot 10^8$	4,096	0.97
16/02/2019 21:44:58	0.88	$7.43 \cdot 10^8$	4,096	0.9
16/02/2019 21:44:59	1.39	$7.31 \cdot 10^8$	$4.51 \cdot 10^5$	0.9
16/02/2019 21:45:00	1.01	$7.44 \cdot 10^8$	4,096	0.9
16/02/2019 21:45:01	0.75	$7.46 \cdot 10^8$	61,440	0.9
16/02/2019 21:45:02	1.26	$7.31 \cdot 10^8$	4,096	0.9
16/02/2019 21:45:03	1.13	$7.44 \cdot 10^8$	4,096	0.82
16/02/2019 21:45:04	5.77	$7.77 \cdot 10^8$	$1.72 \cdot 10^5$	0.82
16/02/2019 21:45:05	9.85	$8.31 \cdot 10^8$	$4.99 \cdot 10^6$	0.82
16/02/2019 21:45:06	3.88	$8.46 \cdot 10^8$	$8.25 \cdot 10^7$	0.82

Data Normalization

- Unrolling

Sample of unrolled data

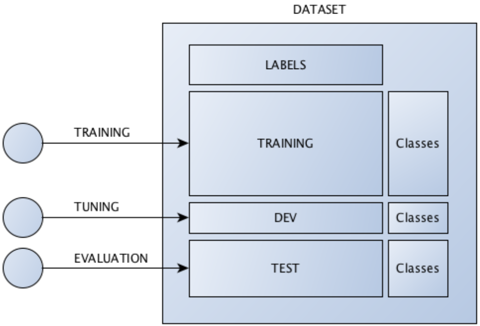
usr1	usr2	usr3	1m1	1m2	1m3
6.1	1.75	1.26	0.97	0.97	0.9
5.9	1.5	3.1	0.9	0.92	0.97
5.8	1.76	2.2	0.89	0.91	0.94

- Normalizing

Sample of normalized data

usr1	usr2	usr3	1m1	1m2	1m3
0.6	0.3	-0.5	0.6	0.6	-0.5
-0.1	-0.7	0.5	-0.3	-0.2	0.5
-0.4	0.3	0	-0.4	-0.4	0

Building the dataset



Structure of a dataset

- Split in training, dev, test
- Obtain classes
- Store normalized data on s3
- Input function for training
- Input function for evaluation

Data Pipelines

Experiment Workflow

- Visualize data
- Define a dataset
- **Define an experiment**
- **Run the training**
- **Collect results**

```
# Define a local experiment
ciml-setup-experiment --experiment dnn-5x100 \
  --estimator tf.estimator.DNNClassifier \
  --hidden-layers 100/100/100/100/100 \
  --steps $(( 2000 / 128 * 500 )) \
  --batch-size 128 \
  --epochs 500 \
  --data-path s3://cimldatasets
```

```
# Train the model locally based on the dataset and experiment
# Store the evaluation metrics as a JSON file
ciml-train-model --dataset cpu-load-1min-dataset \
  --experiment dnn-5x100 \
  --data-path s3://cimldatasets

# Train the same model in a FfDL cluster
ffdl_train.sh cpu-load-1min-dataset dnn-5x100

# Train the same model with a Tekton task
tkn task start ciml-run-training \
  -p dataset=dnn-5x100 \
  -p experiment=cpu-load-1min-dataset
```

Training Infrastructure

- Training via CIML
- ML framework interchangable
  - TensorFlow Estimator API
  - Keras
  - Scikit-learn
- Training Infra
  - Local machine, Local/S3 Storage
  - jupyter Notebook
  - Ffdl Jobs, S3 Storage
  - Tekton Tasks, S3 Storage
  - Kubeflow Pipelines
- Helm Chart for CIML

Prediction

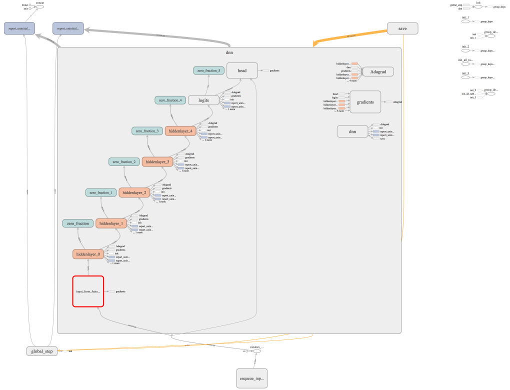
- Event driven: near real time
- MQTT Trigger from the CI system
- CIML produces the prediction
- Example: comment back on Gerrit/Github
- Trusted Source: Continuous Training

- CIML kubernetes app components:
  - MQTT Client receives events
  - Data module fetches and prepares data
  - TensorFlow wrapper issues the prediction

Experiments

DNN - Binary Classification

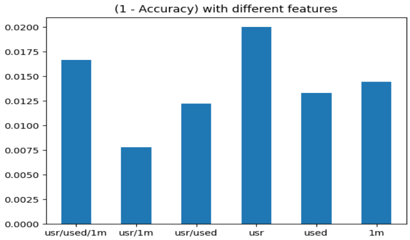
- Classes: Passed or Failed
- Supervised training
- TensorFlow *DNNClassifier*, classes=2
- Dataset:
  - CI Job ”tempest-full”
  - Gate pipeline only
  - 3955 examples split in 60% training, 20% dev and 20% test
- Hyper-parameters:
  - Activation function: ReLU
  - Output layer: Sigmoid
  - Optimizer: Adagrad
  - Learning rate (initial): 0.05
  - 5 hidden layers, 100 units per layer
  - Batch Size: 128, Epochs: 500

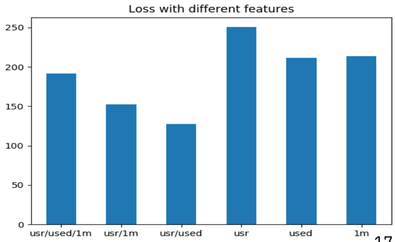


Network Graph - Source: TensorBoard

DNN - Binary Classification

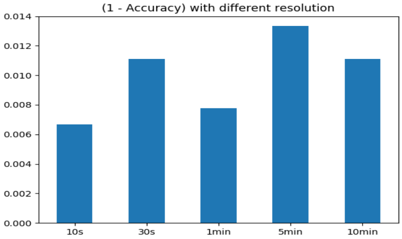
- Selecting the best feature set
- Primary metric: accuracy
- Aim for lower loss, caveat: overfitting
- Key:
  - **usr**: User CPU
  - **used**: Used Memory
  - **1m**: System Load - 1min Average
  - Data Resolution: **1min**
  - Source: TensorFlow evaluation
- Winner: (**usr**, **1m**) tuple
- Accuracy achieved: ***0.992***
- 6 mistakes on a 791 test set

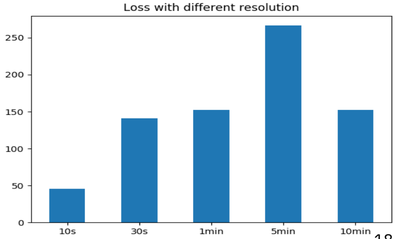




DNN - Binary Classification

- Selecting the data resolution
- Primary metric: accuracy
- Aim for lower loss, caveat: overfitting
- Note: careful with NaN after down-sampling
- Key:
  - Original data frequency: 1s
  - x-axis: new sampling rate
  - Features: (**usr**, **1m**)
  - Source: TensorFlow evaluation
- Winner: **10s**
- Accuracy achieved: ***0.993***
- 6 mistakes on a 791 test set





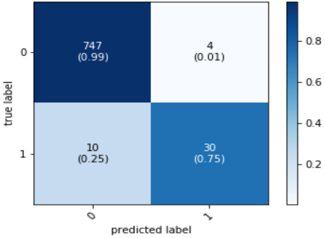
DNN - Binary Classification - Metrics report

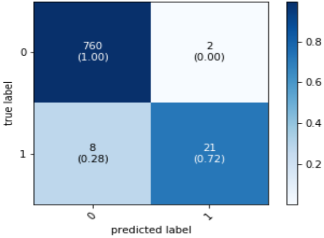
Metrics report for usr 1m and 1min

status	precision	recall	f1-score	support
passed	0.99	0.99	0.99	751
failed	0.88	0.75	0.81	40
accuracy			0.98	791

Metrics report for usr 1m and 10s

status	precision	recall	f1-score	support
passed	0.99	1	0.99	762
failed	0.91	0.72	0.81	29
accuracy			0.99	791





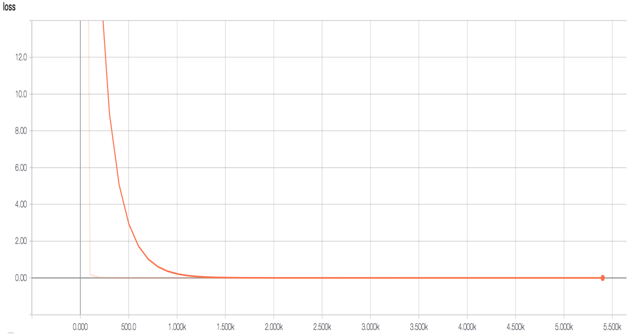
Changing test job

metric	tempest-full	tempest-full-py3
accuracy	0.994	0.953
loss	47.176	86.873
auc_precision_recall	0.949	0.555

- Train with ”tempest-full”
- Evaluating with ”tempest-full-py3”
  - Similar setup, uses python3
  - It does not include swift and swift tests
  - 600 examples evaluation set
- Dataset and training setup:
  - Features: (usr, 1m)
  - Resolution: 1min
  - Same hyper-parameters

Binary Classification - Summary

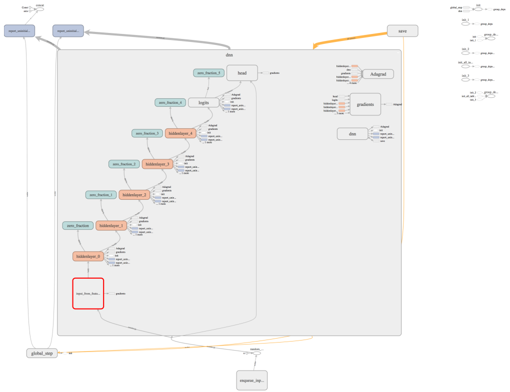
- Features: User CPU and 1min Load Avg
- Resolution: 10s best, 1 minute may be enough
- High accuracy: ***0.993***
- High precision, recall and F1-score
- A trained model might be applicable to similar CI jobs



Training Loss - usr/1m, 1min - Source: TensorBoard

DNN - Multi Class

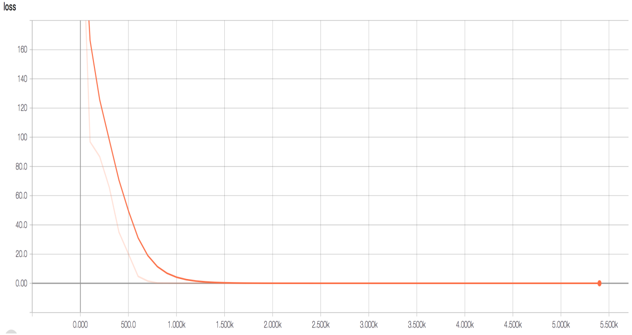
- Classes: Hosting Cloud Provider
- Supervised training
- TensorFlow *DNNClassifier*, classes=**10**
- Dataset:
  - CI Job ”tempest-full”
  - Gate pipeline only
  - 3000 examples, 2100 training, 900 test
- Hyper-parameters:
  - Activation function: ReLU
  - Output layer: Sigmoid
  - Optimizer: Adagrad
  - Learning rate (initial): 0.05
  - 5 hidden layers, 100 units per layer
  - Batch Size: 128, Epochs: 500



Network Graph - Source: TensorBoard

DNN - Multi Class

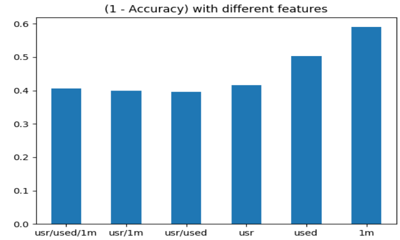
- Features: (usr, 1m)
- Resolution: 1min
- Loss converges, but...
- Evaluation accuracy achieved: ***0.601***
- Not good!

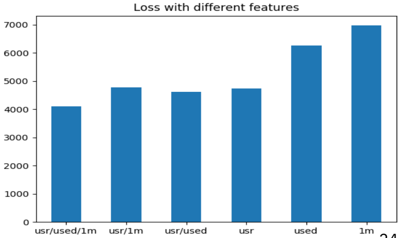


Training Loss - usr/1m, 1min - Source: TensorBoard

Multi Class - Different Features

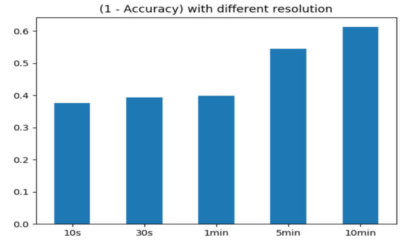
- Try different combinations of features
- Primary metric: accuracy
- Aim for lower loss, caveat: overfitting
- Key:
  - **usr**: User CPU
  - **used**: Used Memory
  - **1m**: System Load - 1min Average
  - Data Resolution: **1min**
  - Source: TensorFlow evaluation output
- No real improvement
- Best accuracy achieved: ***0.603***
- Adding Disk I/O or process data does not help either

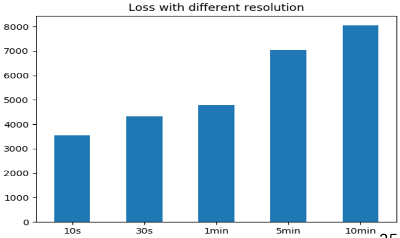




Multi Class - Changing Resolution

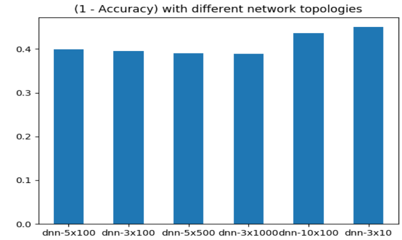
- Trying to change the data resolution
- Primary metric: accuracy
- Aim for lower loss, caveat: overfitting
- Key:
  - Original data frequency: 1s
  - x-axis: new sampling rate
  - Features: (**usr**, **1m**)
  - Source: TensorFlow evaluation
- No real improvement
- Best accuracy achieved: ***0.624***

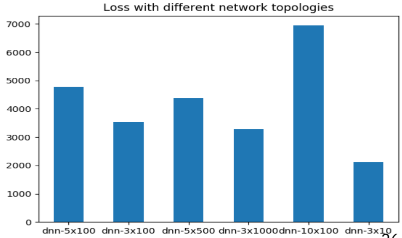




Multi Class - Network topology

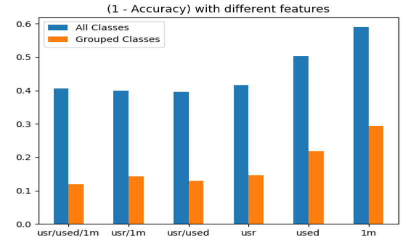
- Trying to change the network depth
- Trying to change number of units per layer
- Primary metric: accuracy
- Aim for lower loss, caveat: overfitting
- Key:
  - x-axis: units and hidden layers
  - Features: (**usr**, **1m**)
  - Resolution: **1min**
  - Source: TensorFlow evaluation
- No real improvement
- Best accuracy achieved: ***0.668***

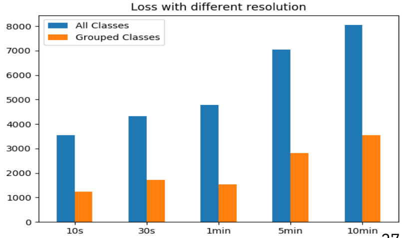




Multi Class - Reducing the number of classes

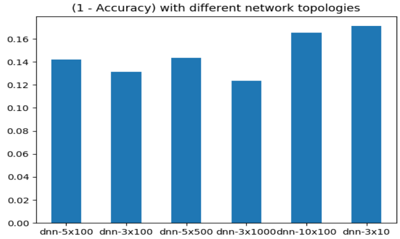
- Reducing the number of classes
  - Different regions from a Cloud Operator
  - Consider as a single class
  - New number of classes is **7**
- Experiments:
  - Train with different feature sets
  - Train with different resolutions
  - Source: TensorFlow evaluation
- Significant improvement!
- Best accuracy achieved: ***0.902***
- What does that mean?

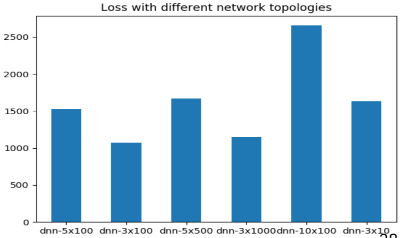




Multi Class - Tuning network topology

- Tuning network topology
- Experiments:
  - x-axis: units and hidden layers
  - Features: (**usr, 1m**)
  - Resolution: **1min**
- Some improvement
- Winner: 3x100. Accuracy: ***0.925***



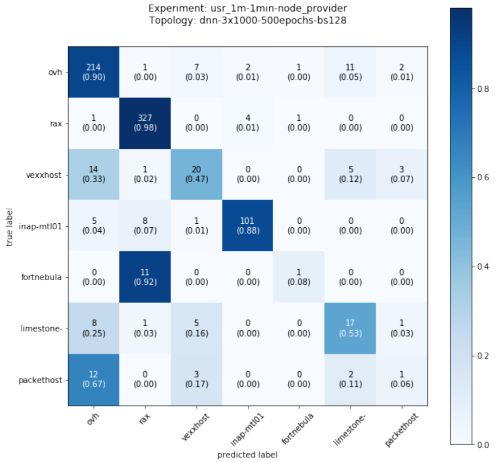


Multi Class - Metrics report

- Experiment:
  - Dataset: 3955 examples split in 60% training, 20% dev and 20% test
  - Features: User CPU and Load Avg
  - Resolution: 1 minute
  - Hyperparameters: 3 hidden layers, 1000 units each
  - Cloud providers: 7

Metrics report for usr 1m and 1min

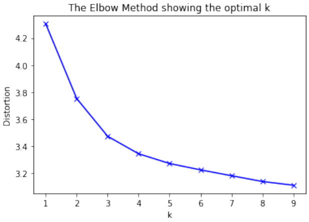
provider	precision	recall	f1-score	support
rax	0.94	0.98	0.96	333
inap-mtl01	0.94	0.88	0.91	115
ovh	0.84	0.9	0.87	238
vexxhost	0.56	0.47	0.51	43
limestone	0.49	0.53	0.51	32
fortnebula	0.33	$8 \cdot 10^{-2}$	0.13	12
packethost	0.14	$6 \cdot 10^{-2}$	$8 \cdot 10^{-2}$	18
accuracy			0.86	791



Multi Class - Clustering

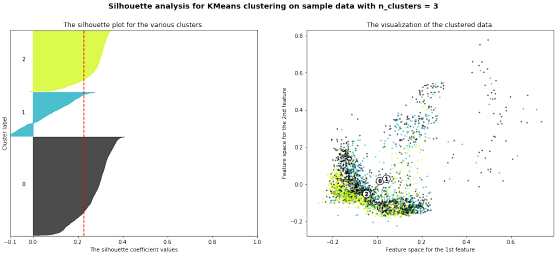
- Unsupervised learning on multiclass dataset
- Dataset: features CPU, Avg.load; resolution 10s
- Algorithm: kmeans
- Number of clusters based on elbow method and silhouette score
- Recommended number of clusters: 3 to 4
- Fits with the number of providers with most examples in dataset

class	provider	examples
2	rax	1,208
6	inap-mtl01	807
1	ovh	377
0	vexxhost	173
5	limestone	120
3	packethost	57
4	fortnebula	31

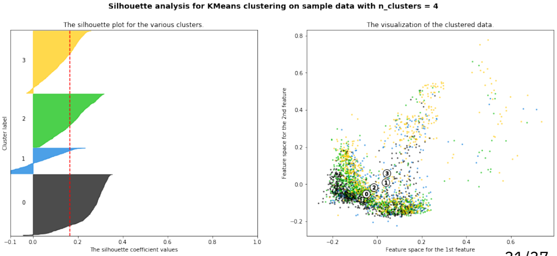


Multi Class - Clustering

cluster	classes	example	pclass	pcluster
0	1	374	99.2%	27.8%
	2	795	65.8%	59.2%
	3	47	82.5%	3.5%
1	5	68	56.7%	11.3%
2	6	768	95.2%	92.6%

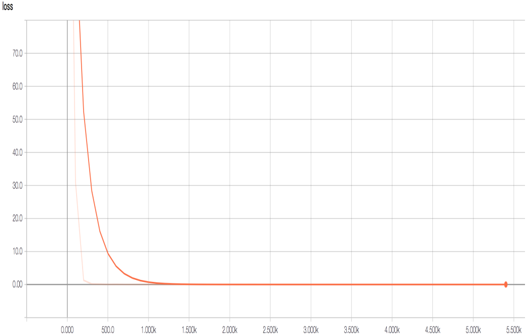


cluster	class	example	pclass	pcluster
0	6	771	95.5%	92.3%
1	5	64	53.3%	25.4%
2	1	349	92.6%	47.7%
3	2	772	63.9%	90.4%



Multi Class - Summary

- User CPU and 1min Load Avg
- Resolution: 1 minute is enough
- Hyperparameters: 3 hidden layers, 100 units each
- Reasonable accuracy: ***0.925***
- System data can be used to cluster cloud providers
- Higher support helps for better clustering
- A trained model is not applicable to similar CI jobs



Training Loss - usr/1m, 1min, dnn3x100 - Source: TensorBoard

Conclusions

Conclusions

- Collect data
- Know your data
- Work with cloud tools
- Able to confirm that system load plays a role in failures
- Load profiles are consistent across regions in our cloud providers

Future Work

- Clustering of Cloud Provider Inap is especially accurate
  - What is special about this Cloud Provider?
- Extend dataset to include system/application logs
- Explore clustering of failed jobs
- Explore job portability

Questions?

- This talk: https://github.com/afrittoli/ciml_talk
- CIML: https://github.com/mtreinish/ciml

Thank You!