

Machine Learning for CI



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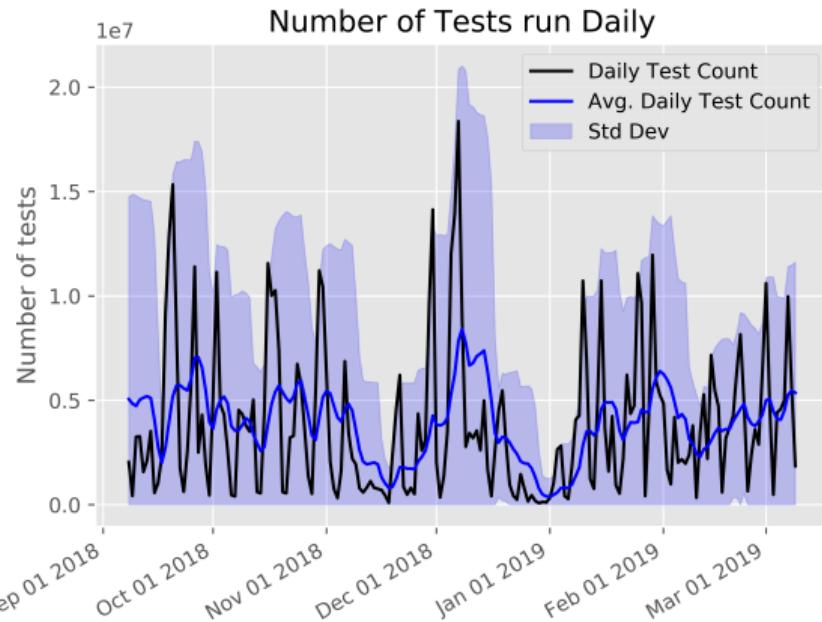
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Data Sourcing



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CI at Scale



Source: subunit2sql-graph dailycount

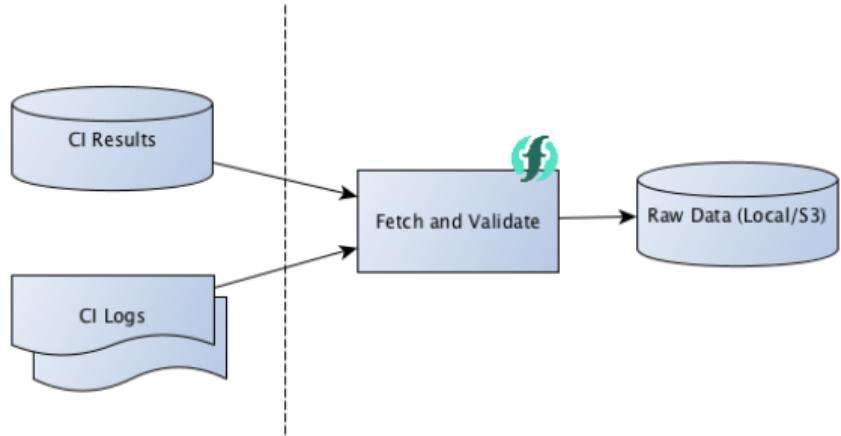
- Continuous Integration
- Continuous Log Data
- Lots of data, little time
- Triaging failures?
- AI to the rescue!

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



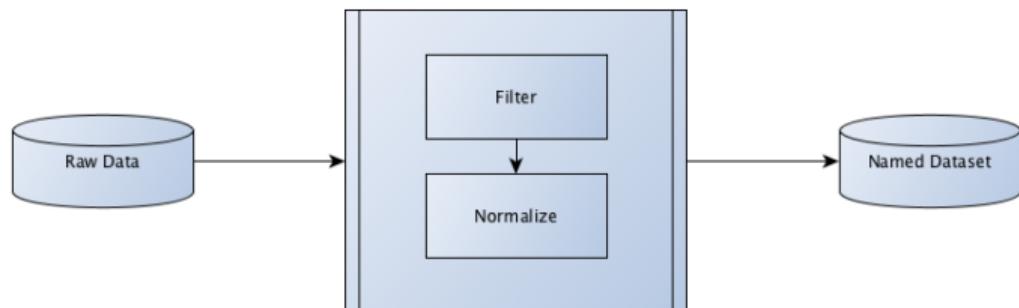
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Experiment Workflow

- **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
- Normalizing

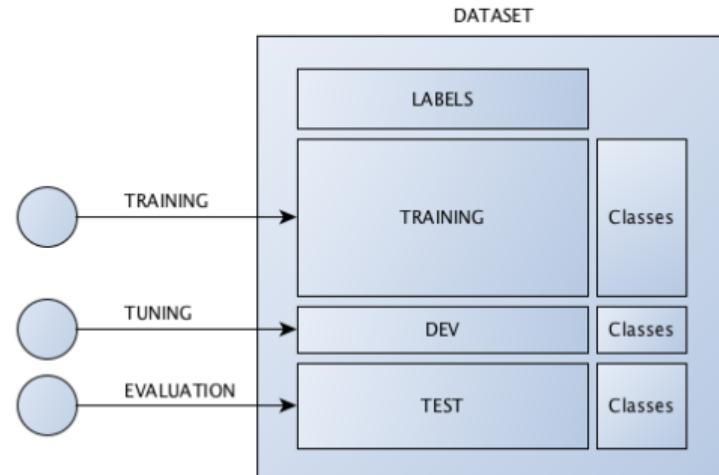
Sample of unrolled data

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

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
```

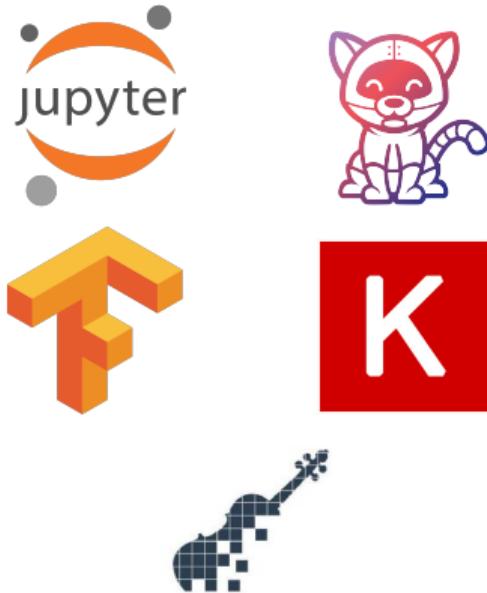
```
# Train the model locally based on the dataset and experiment
# Store the evaluation metrics as a JSON file
ciml-train-model —dataset cpu-load-1min-dataset \
    —experiment dnn-5x100 \
    —data-path s3://cimldatasets
```

```
# Train the same model in a FfDL cluster
ffd1_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 interchangeable
 - 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

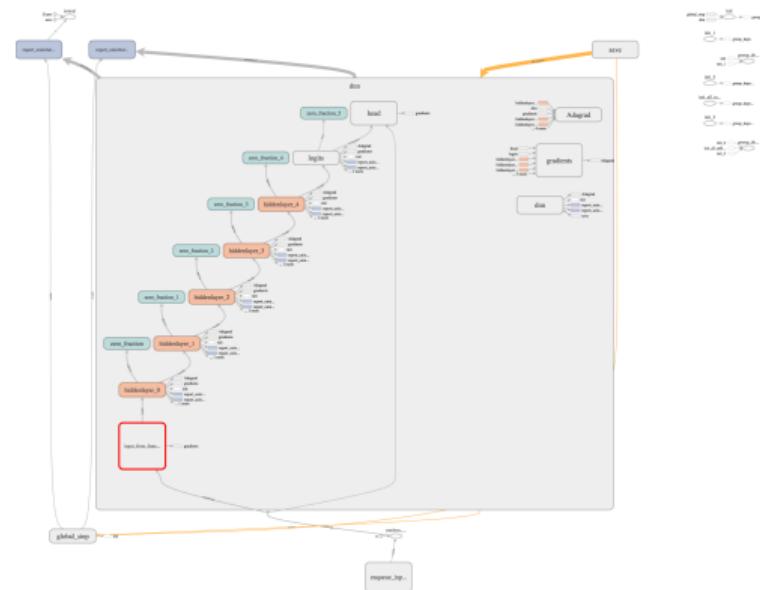
- Event driven: near real time
 - MQTT Trigger from the CI system
 - CIML produces the prediction
 - Example: comment back on
Gerrit/Github
 - Trusted Source: Continuous Training
-
- CIML kubernetes app components:
 - MQTT Client receives events
 - Data module fetches and prepares data
 - TensorFlow wrapper issues the prediction

— Experiments



DNN - Binary Classification

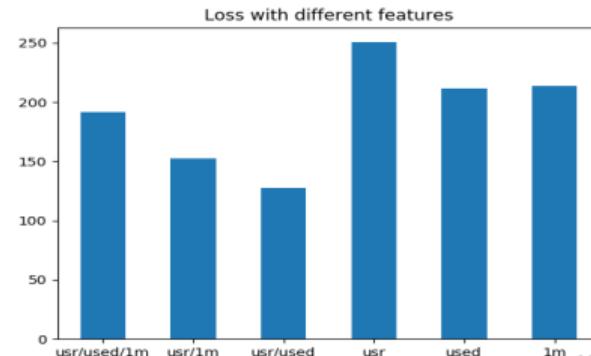
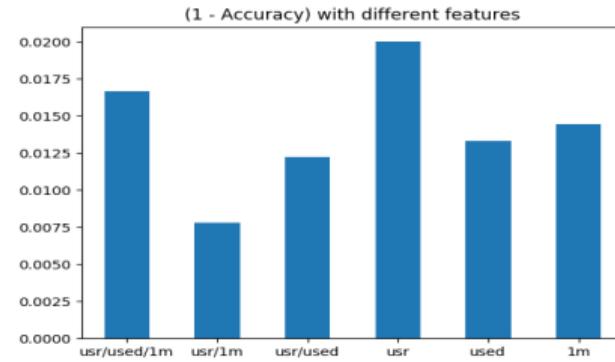
- Classes: Passed or Failed
- Supervised training
- TensorFlow *DNNClassifier*, classes=2
- Dataset:
 - CI Job "tempest-full"
 - Gate pipeline only
 - 3955 examples split in 60% training, 20% dev and 20% test
- Hyper-parameters:
 - Activation function: ReLU
 - Output layer: Sigmoid
 - Optimizer: Adagrad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



Network Graph - Source: TensorBoard

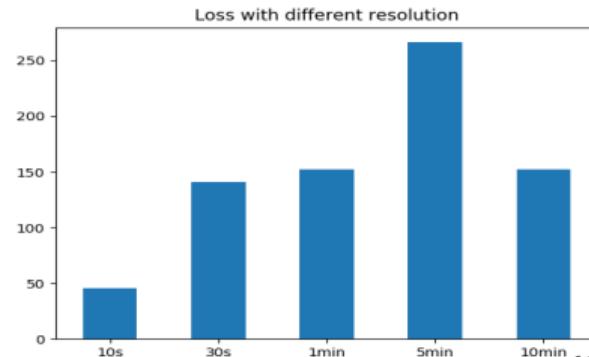
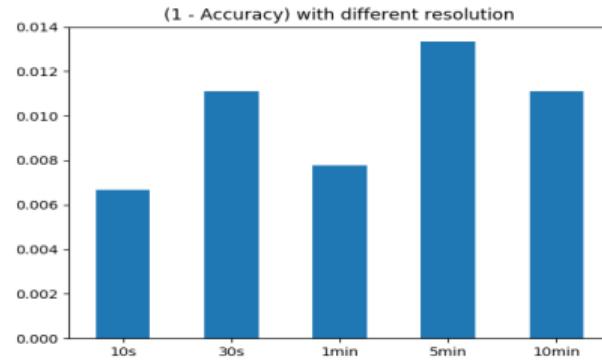
DNN - Binary Classification

- 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

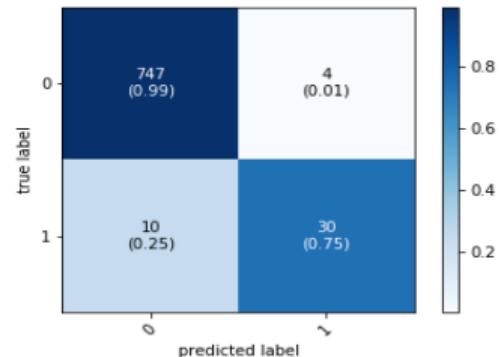
- Selecting the data resolution
- Primary metric: accuracy
- Aim for lower loss, caveat: overfitting
- Note: careful with NaN after down-sampling
- Key:
 - Original data frequency: 1s
 - x-axis: new sampling rate
 - Features: (**usr, 1m**)
 - Source: TensorFlow evaluation
- Winner: **10s**
- Accuracy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



DNN - Binary Classification - Metrics report

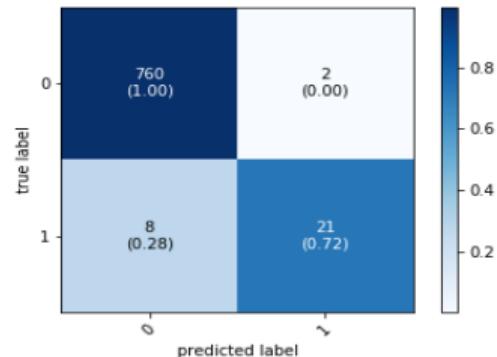
Metrics report for usr 1m and 1min

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	



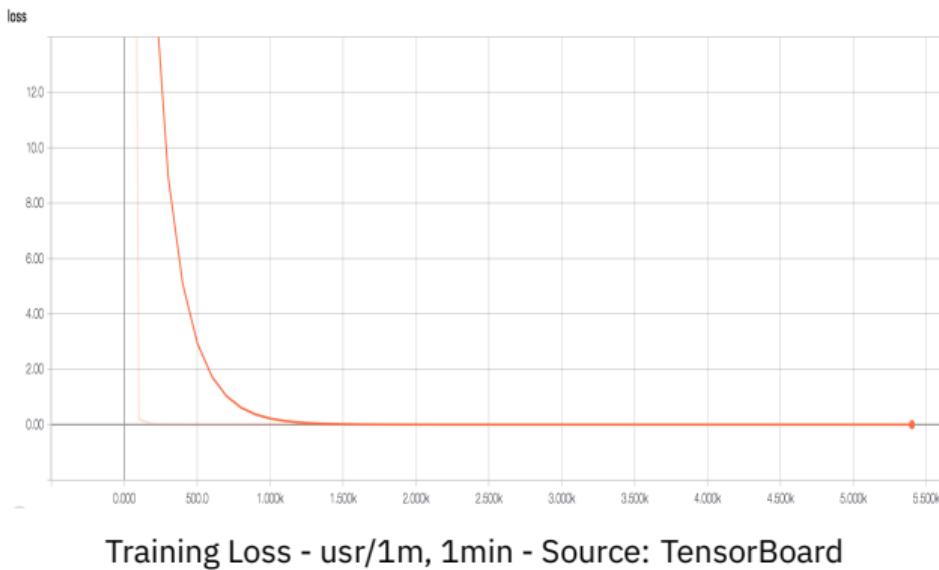
Changing test job

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

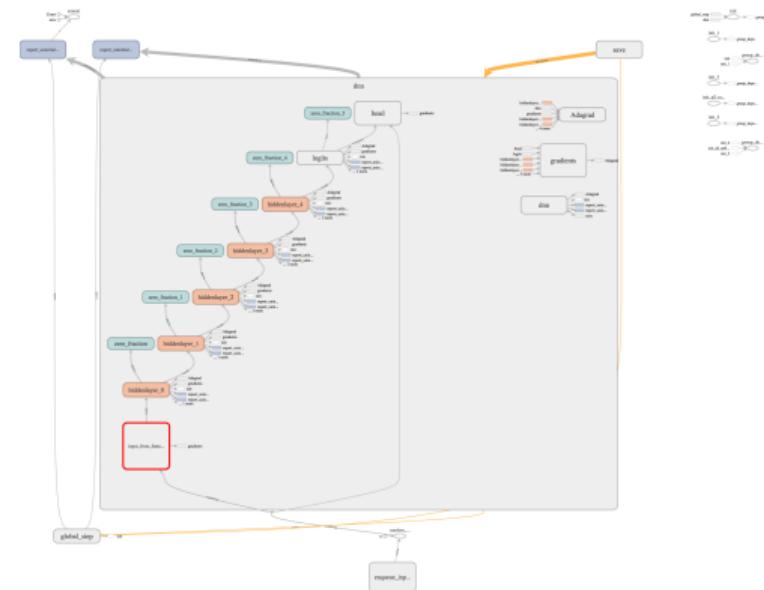
Binary Classification - Summary

- 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



DNN - Multi Class

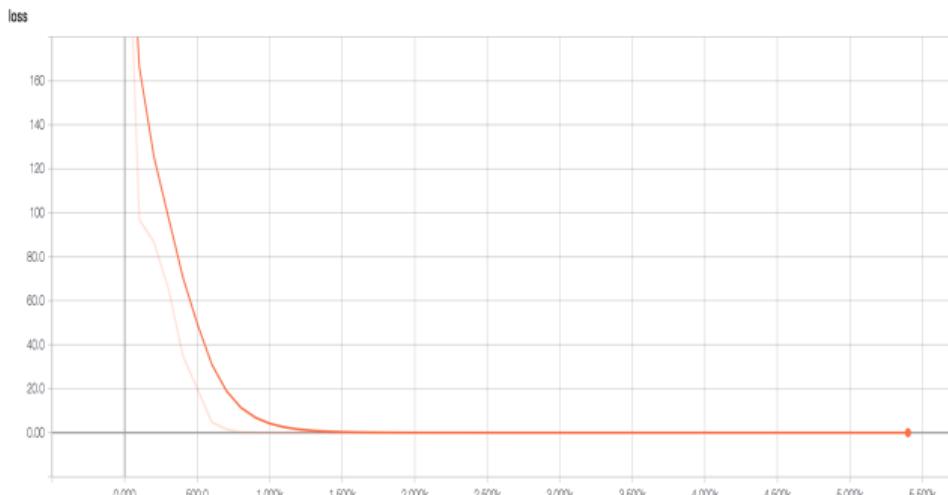
- Classes: Hosting Cloud Provider
- Supervised training
- TensorFlow *DNNClassifier*, classes=**10**
- Dataset:
 - CI Job "tempest-full"
 - Gate pipeline only
 - 3000 examples, 2100 training, 900 test
- Hyper-parameters:
 - Activation function: ReLU
 - Output layer: Sigmoid
 - Optimizer: Adagrad
 - Learning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



Network Graph - Source: TensorBoard

DNN - Multi Class

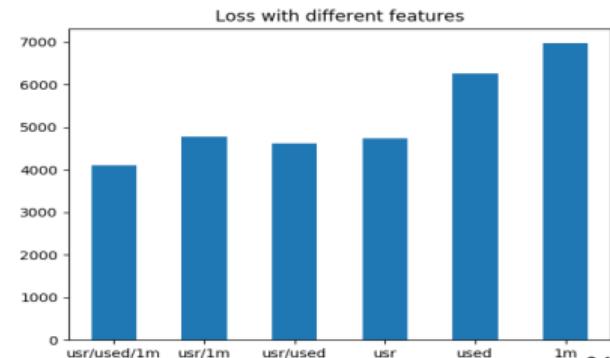
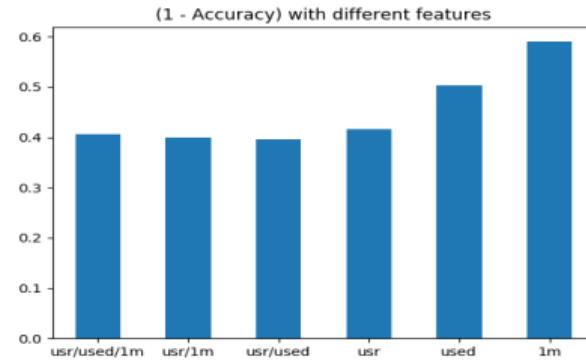
- Features: (usr, 1m)
- Resolution: 1min
- Loss converges, but...
- Evaluation accuracy achieved:
0.601
- Not good!



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

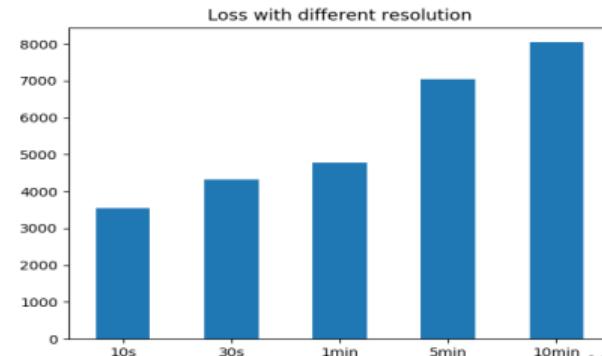
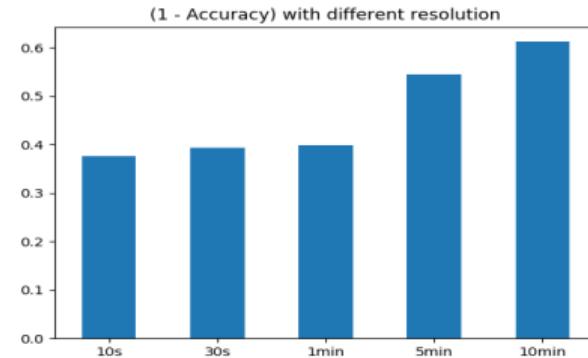
Multi Class - Different Features

- 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



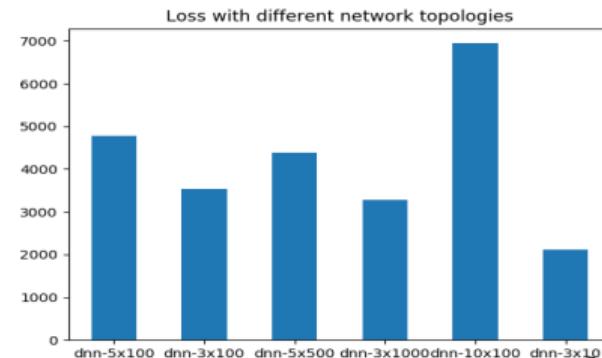
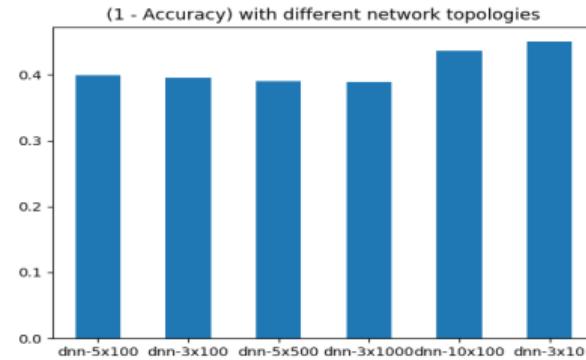
Multi Class - Changing Resolution

- 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**



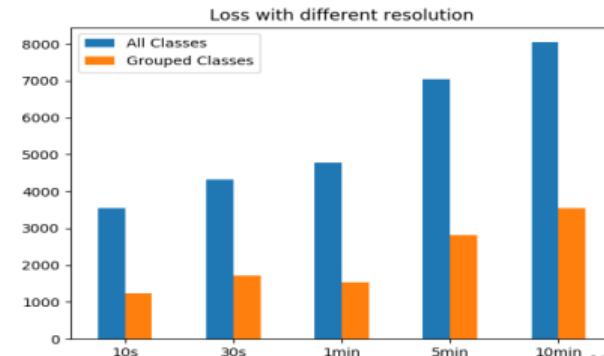
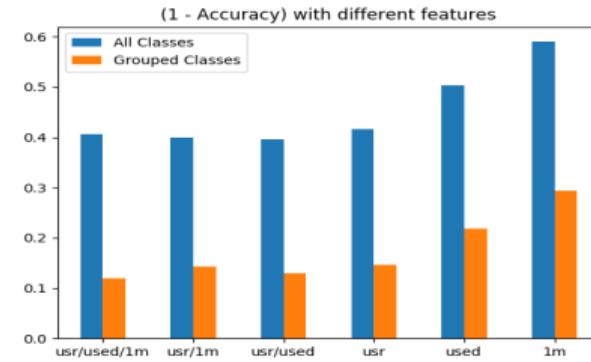
Multi Class - Network topology

- 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**



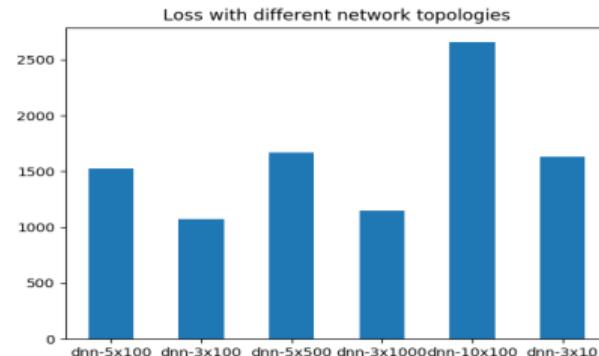
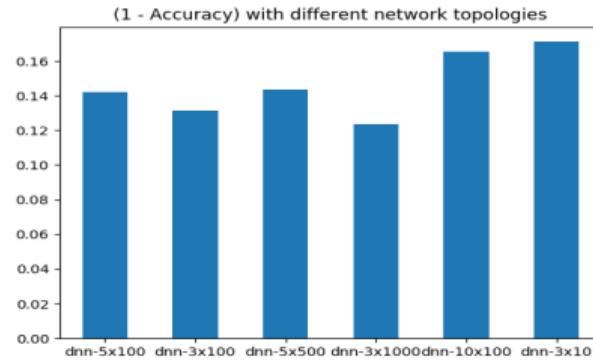
Multi Class - Reducing the number of classes

- 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**



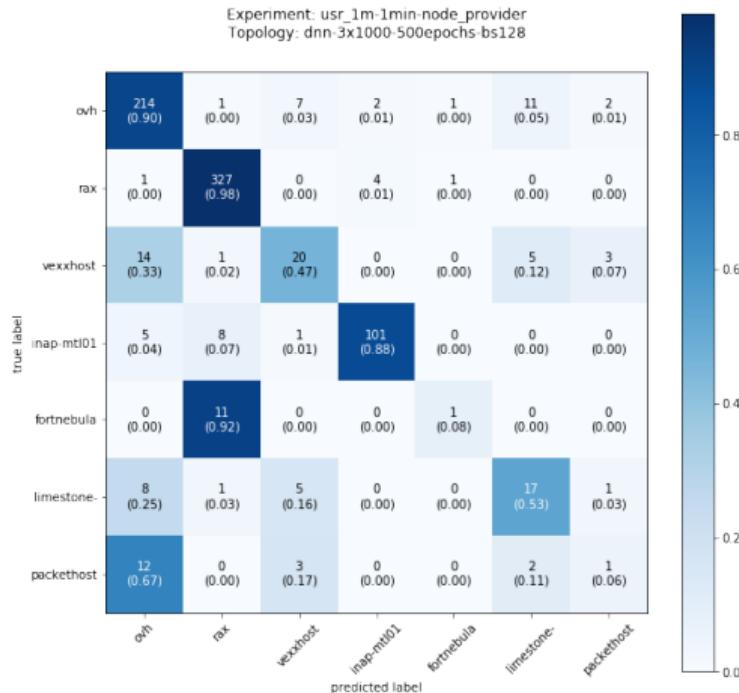
Multi Class - Metrics report

– 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

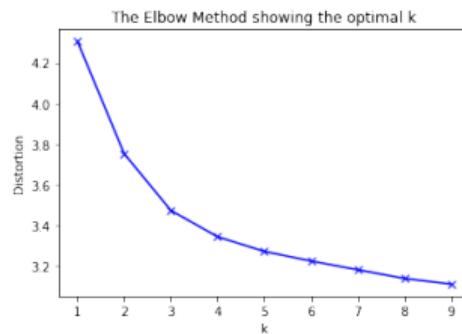
provider	precision	recall	f1-score	support
rax	0.94	0.98	0.96	333
inap-mtl01	0.94	0.88	0.91	115
ovh	0.84	0.9	0.87	238
vexxhost	0.56	0.47	0.51	43
limestone	0.49	0.53	0.51	32
fortnebula	0.33	$8 \cdot 10^{-2}$	0.13	12
packethost	0.14	$6 \cdot 10^{-2}$	$8 \cdot 10^{-2}$	18
accuracy			0.86	791



Multi Class - Clustering

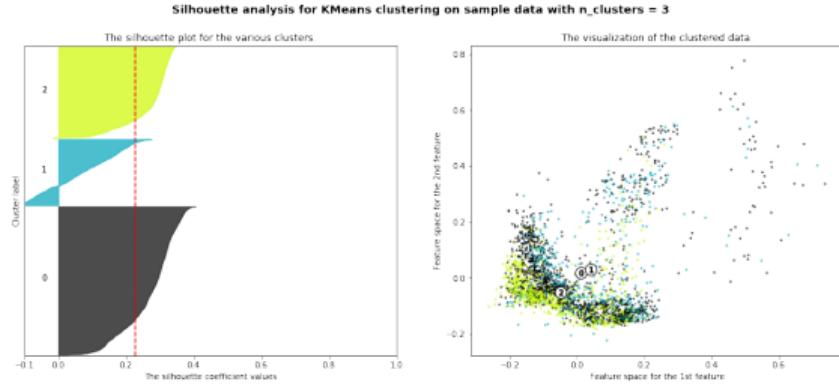
- Unsupervised learning on multiclass dataset
- Dataset: features CPU, Avg.load; resolution 10s
- Algorithm: kmeans
- Number of clusters based on elbow method and silhouette score
- Recommended number of clusters: 3 to 4
- Fits with the number of providers with most examples in dataset

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

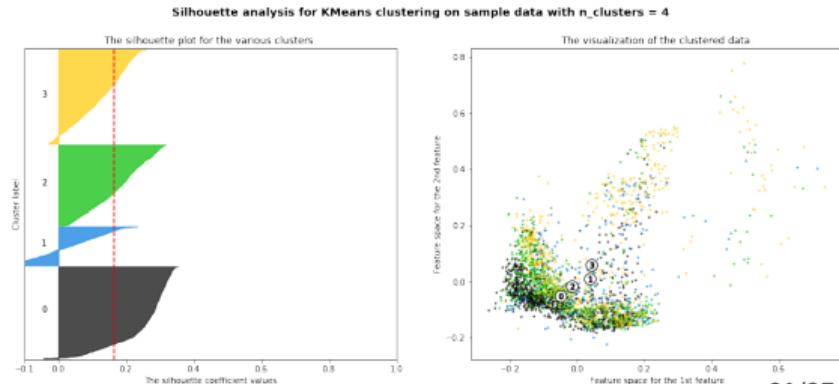


Multi Class - Clustering

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%

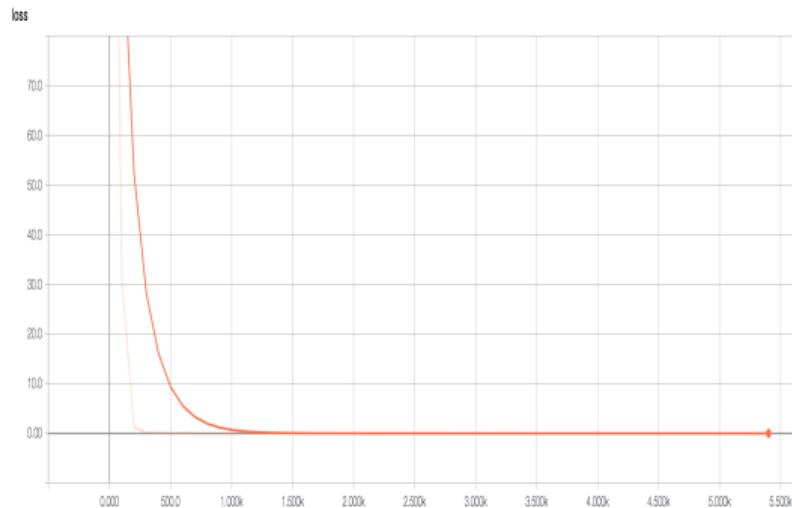


cluster	class	example	pclass	pcluster
0	6	771	95.5%	92.3%
	5	64	53.3%	25.4%
2	1	349	92.6%	47.7%
3	2	772	63.9%	90.4%



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 CP inap is accurate, what is special about this CP?
- 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!