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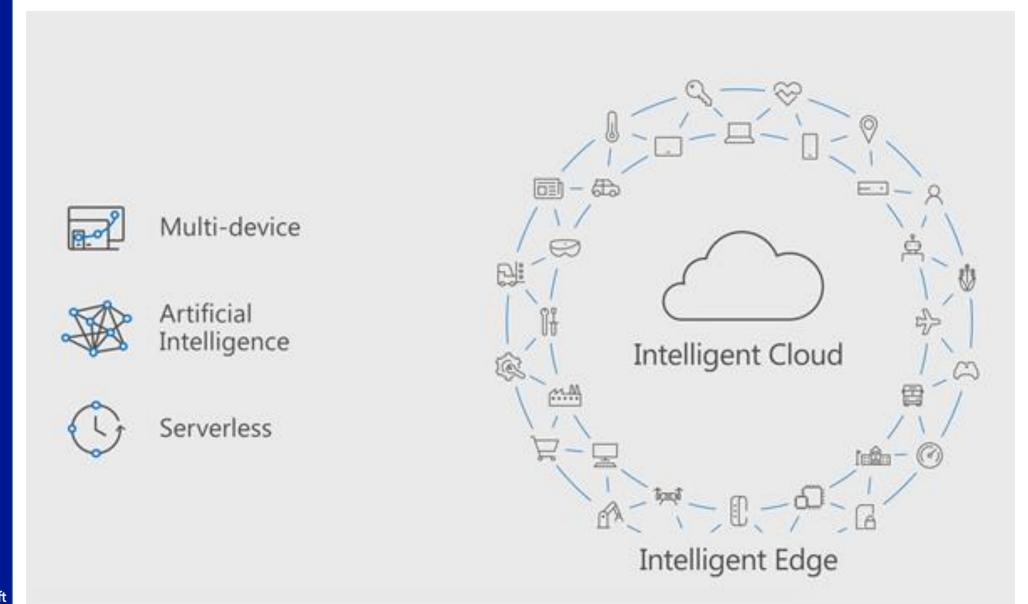


### Agenda

- ☐ Intelligent Application Architecture and Services
- Deep Neural Networks
- DNN DevOps Environments
- Recurrent Neural Network
- ☐ Long Short Term Memory Network
- □ LSTM for Predictive Maintenance
- ☐ LSTM in Python

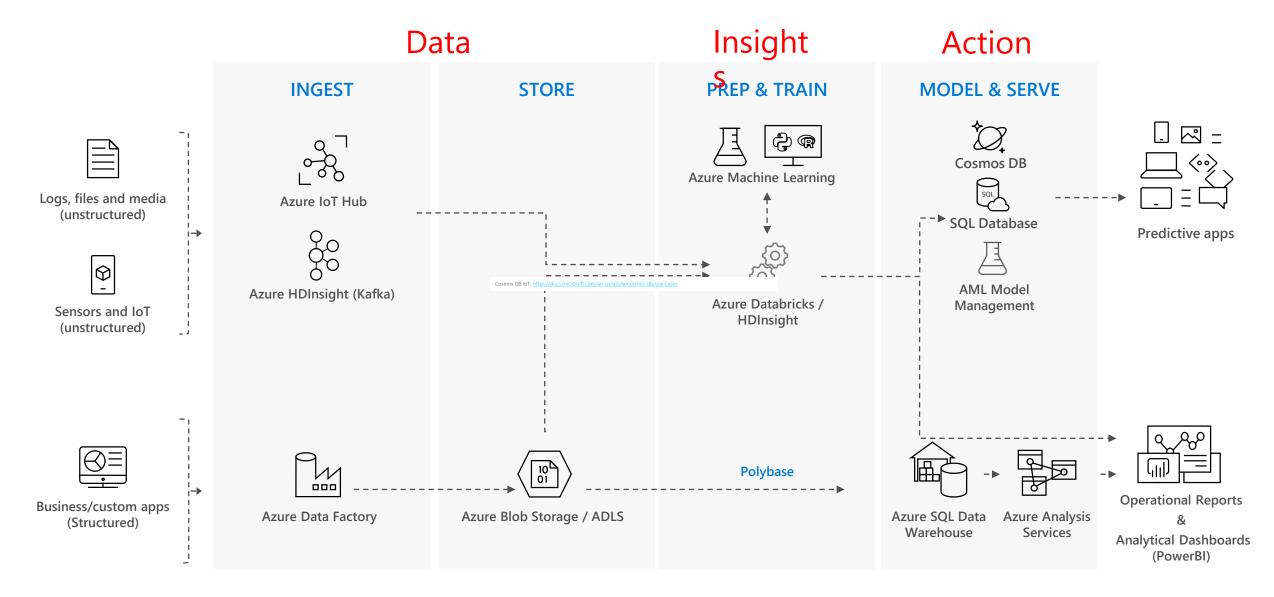


# Intelligent Cloud & Intelligent Edge





#### INTELLIGENT APPLICATIONS



Cosmos DB IoT: <a href="https://docs.microsoft.com/en-us/azure/cosmos-db/use-cases">https://docs.microsoft.com/en-us/azure/cosmos-db/use-cases</a>

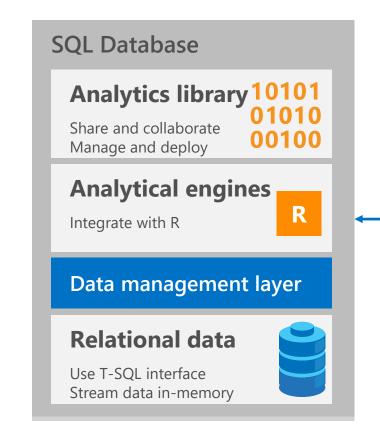
# SQL Database with Machine Learning Services

R integration enables end to end machine learning in Azure SQL Database – without moving data

Operationalize your machine learning scripts and models directly in a fully managed database in the cloud.

Expose predictions to any application using your database, easily and seamlessly.

Take advantage of predictions via simple stored procedures for apps connecting to SQL Database.



#### **Data scientists**

Publish algorithms, interact directly with data

#### **DBAs**

Manage storage and analytics together

#### **Business analysts**

Analyze through T-SQL, tools, and vetted algorithms











### Azure SQL Data Warehouse

Compute Optimized Gen 2 is now Generally Availble

**5 times** the performance of our Gen1 offer

4 times the concurrency up to 128 concurrent queries – the highest of any cloud data warehousing service

**5 times** the compute headroom (over 4000 compute cores)

Infinite storage of columnar data









Seamlessly compatible across Microsoft and other leading BI & Data Integration services







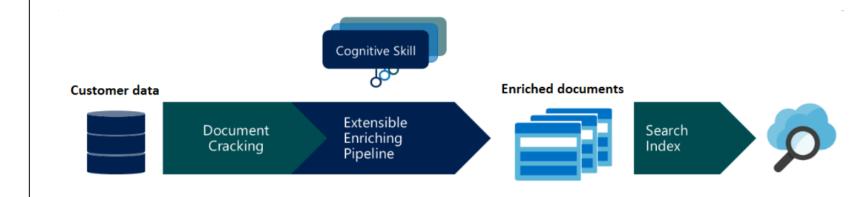




# Cognitive Search

Cognitive Search is an enrichment pipeline that transforms raw, unstructured content into rich searchable content in an Azure Search index

- Find structured information from unstructured data
- Powered by cognitive skills, such as natural language processing and computer vision capabilities
- Extracts structure and semantics from unstructured and non-textual data, and feeds it into a search index













# Al Translation & Application: Cognitive Services

#### Use AI to solve business problems



#### Vision

Image-processing algorithms to smartly identify, caption and moderate your pictures.



#### Speech

Convert spoken audio into text, use voice for verification, or add speaker recognition to your app.



#### Knowledge

Map complex information and data in order to solve tasks such as intelligent recommendations and semantic search.



#### Search

Add Bing Search APIs to your apps and harness the ability to comb billions of webpages, images, videos, and news with a single API call.



#### Language

Allow your apps to process natural language with pre-built scripts, evaluate sentiment and learn how to recognize what users want.





# Al Face for Your Company: BOT



#### Accelerated development

Azure Bot Service speeds up development by providing an integrated environment that's purpose-built for bot development with the Microsoft Bot Framework connectors and BotBuilder SDKs. Developers can get started in seconds with out-of-the-box templates for scenarios including basic, form, language understanding, question and answer, and proactive bots.

#### Give your bot intelligence with Cognitive Services

Give your bot some super powers. Go beyond a great conversationalist to a bot that can recognize a user in photos, moderate content, make smart recommendations, translate language and more. Cognitive Services enable your bot to see, hear, and interpret in more human ways.





















#### Engage your audience, wherever they are

Your users talk in many places, your bot should too. Azure Bot Service can be integrated across multiple channels to increase interactions and reach more customers using your website or app to email, GroupMe, Facebook Messenger, Kik, Skype, Slack, Microsoft Teams, Telegram, text/SMS, Twilio, Cortana, and Skype for Business.



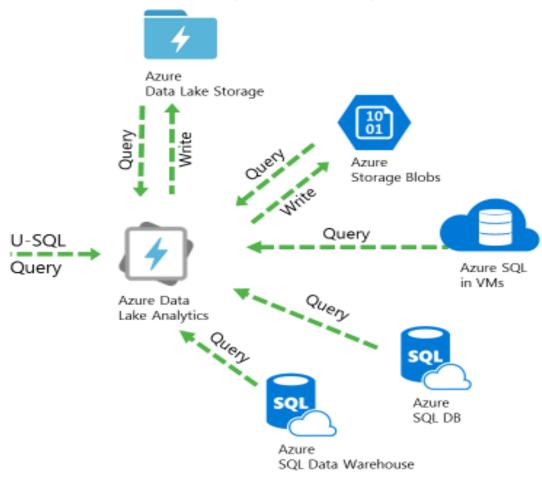
## Data Lake Store & Analytics

### Query data where it lives

Easily query data in multiple Azure data stores without moving it to a single store

#### **Benefits**

- Avoid moving large amounts of data across the network between stores
- Single view of data irrespective of physical location
- Minimize data proliferation issues caused by maintaining multiple copies
- Single query language for all data
- Each data store maintains its own sovereignty
- Design choices based on the need
- Push SQL expressions to remote SQL sources
  - Filters
  - Joins



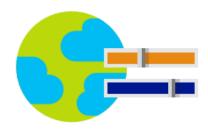
### Cosmos DB



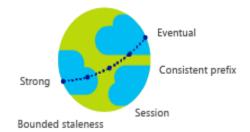
Turnkey global distribution



Multi-model + multi-API: SQL, JavaScript, Gremlin, MongoDB, Cassandra



Limitless elastic scale around the globe



Multiple, well-defined consistency choices



Guaranteed low latency worldwide: R/W: 10/15 millisecond at 99 percentile

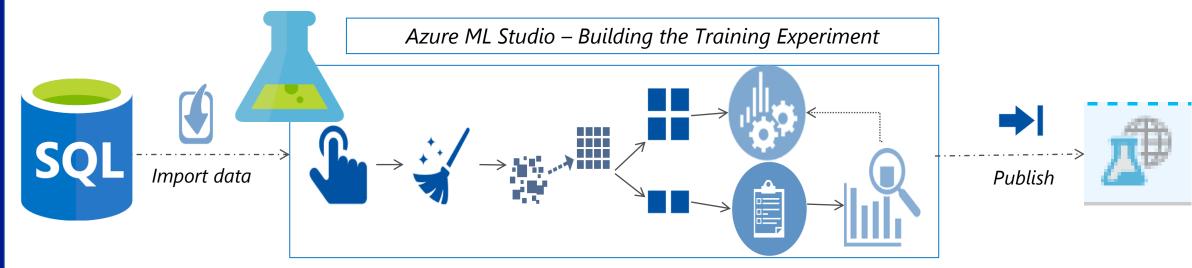


Industry-leading, enterprise-grade SLAs



# Azure Machine Learning Studio/Workbench

**Objective:** Predict engine failure for preventive maintenance based on sensor data and failure history data



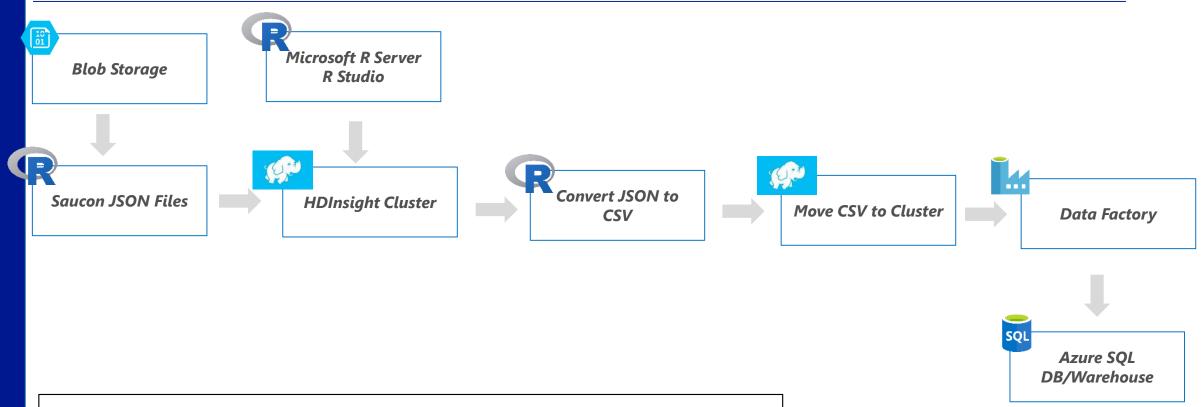
Select -> clean -> transform -> split -> train -> score -> evaluate

- ✓ Front End tool for doing Predictive Modelling
- ✓ Automatic Algorithm Selection
- ✓ Use of Open source languages like R and Python





# Azure HDInsight with R Studio



- ✓ How raw data is stored and managed
- ✓ How the raw data is ingested, cleansed, transformed and prepared
- ✓ Performance of Large Datasets





# Demo

# Introducing Microsoft Power BI

#### Key benefits and differentiators



Pre-built content packs, consisting of dashboards and reports, for popular SaaS solutions



Real-time dashboard updates



Secure, live connection to your data sources, on-premises and in the cloud



Intuitive data exploration by using natural language query



Integration with familiar Microsoft products, and commitment for scale and availability in Azure



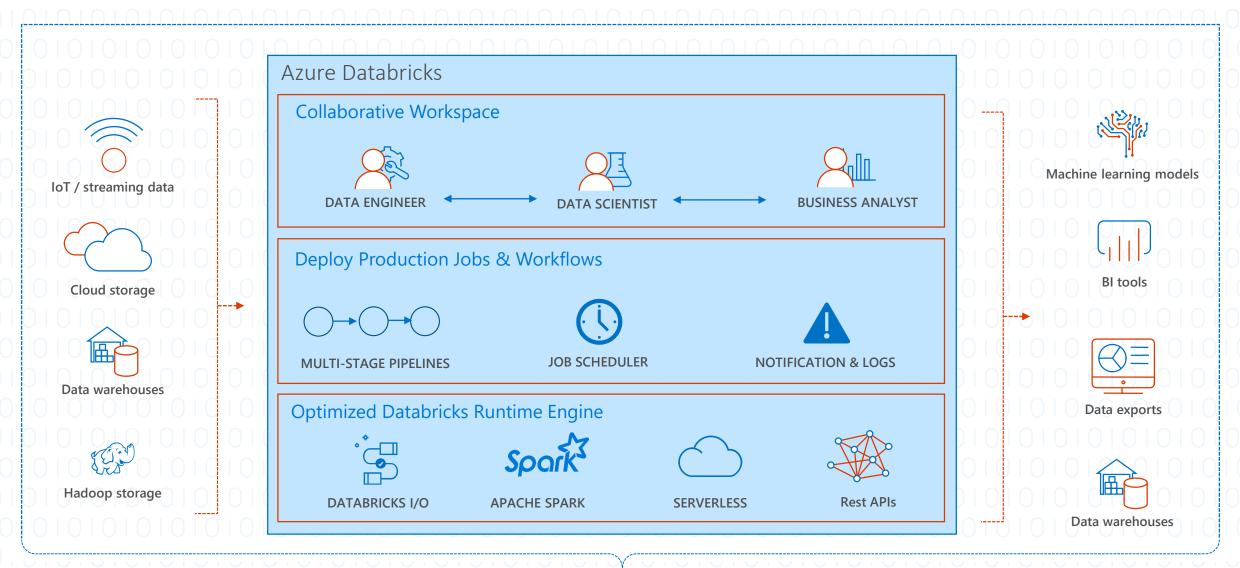
Fast deployment, hybrid configuration, secure, and integrated with existing IT systems







#### AZURE DATABRICKS



#### AZURE DATABRICKS ACCESS CONTROL

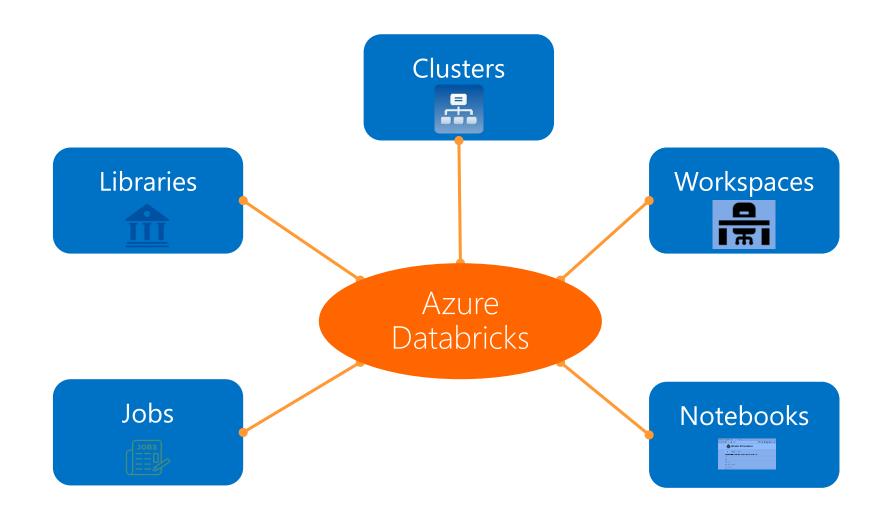
Access control can be defined at the user level via the AAD

Access Control can be defined for Workspaces, Clusters, Jobs and REST APIs

4	
Workspace Access Control	Defines who can who can view, edit, and run notebooks in their workspace
Cluster Access Control	Allows users to who can attach to, restart, and manage (resize/delete) clusters.
Cluster Access Control	Allows Admins to specify which users have permissions to create clusters
Jobs Access Control	Allows owners of a job to control who can view job results or manage runs of a job (run now/cancel)
REST API Tokens	Allows users to use personal access tokens instead of passwords to access the Databricks REST API

Databricks Access Control

#### AZURE DATABRICKS CORE ARTIFACTS



# Deep Neural Network

- DNNs for speaker recognition in the 1990s.
- Speech recognition around 2009-2011
- LSTM around 2003-2007
- Today: accelerated progress in eight major areas.
  - CNN (Convolutional neural networks) and how to design them to best exploit domain knowledge of speech/image
  - RNN (Recurrent Neural Networks) and its LSTM(Long

Short Term Memory) variants Deep learning - Related People



Andrew Ng







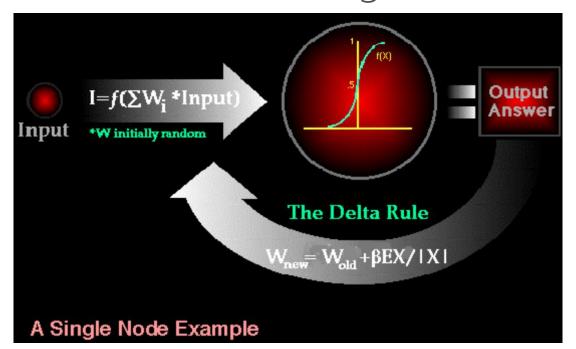
**Geoffrey Hinton** 

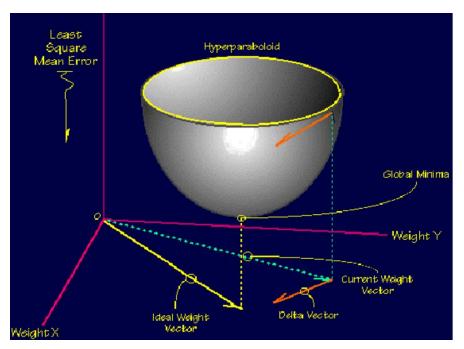
Yann LeCun



## Artificial Neuron Network (1960-1998)

- ANNs are organized in layers and made up of a number of interconnected 'nodes' which contain an 'activation fun
- ANNs contain some form of 'learning rule' which modifies the weights.

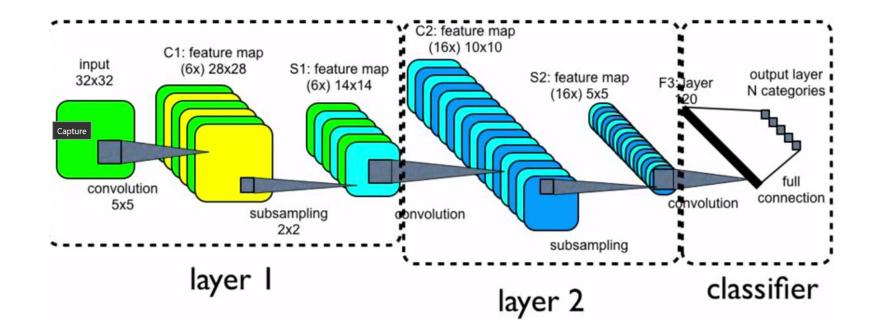






### Convolutional Neural Networks (CNN)

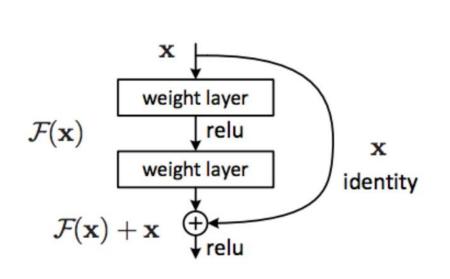
- Individual *neurons* respond to *stimuli* only in a restricted region of the *receptive field*.
- The receptive fields of different neurons partially overlap and cover entire visual field.

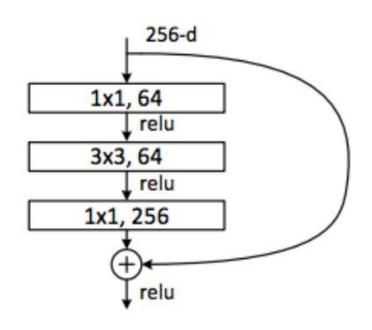




### Residual Neural Networks (ResNet)

- ResNets skip connections or short-cuts to jump over some layers.
- With several parallel skips it is referred to as DenseNets.

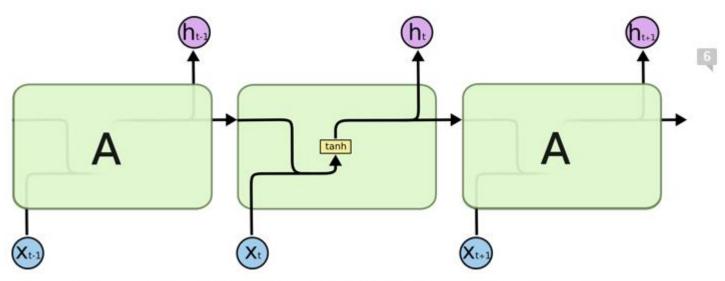






### Recurrent Neural Networks (RNN)

- All RNNs have the form of a chain of repeating modules of neural network.
- This repeating modules have a very simple structure, such as a single tanh layer.







### Basic Theorems: 1 of 3

 Neural Networks define a class of "universal approximators" (Cybenko 1989 and Hornik 1991)

**Theorem** [C'89, H'91] Let  $\rho()$  be a bounded, non-constant continuous function. Let  $I_m$  denote the m-dimensional hypercube, and  $C(I_m)$  denote the space of continuous functions on  $I_m$ . Given any  $f \in C(I_m)$  and  $\epsilon > 0$ , there exists N > 0 and  $v_i, w_i, b_i, i = 1 \dots, N$  such that

$$F(x) = \sum_{i \le N} v_i \rho(w_i^T x + b_i) \text{ satisfies}$$

$$\sup_{x \in I_m} |f(x) - F(x)| < \epsilon .$$



### Basic Theorems: 2 of 3

Neural Network Estimation Theory (Barron 1992)

**Theorem** [Barron'92] The mean integrated square error between the estimated network  $\hat{F}$  and the target function f is bounded by

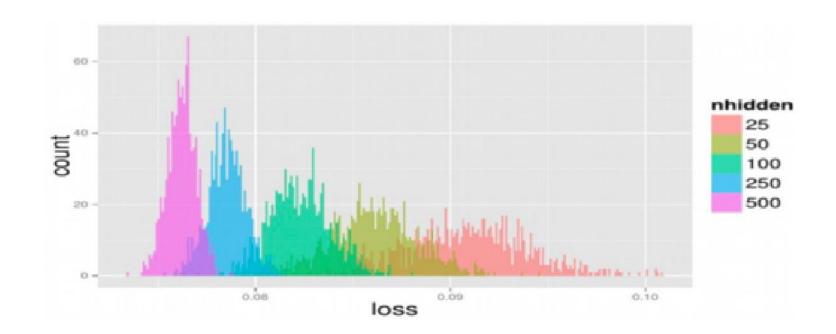
$$O\left(\frac{C_f^2}{N}\right) + O\left(\frac{Nm}{K}\log K\right) ,$$

where K is the number of training points, N is the number of neurons, m is the input dimension, and  $C_f$  measures the global smoothness of f.



### Basic Theorems: 3 of 3

• Using tools from Statistical Physics to explain the behavior of stochastic gradient methods when training DNN (Dauphin @ ICML 2015)





#### Demo

- We run the same example in three ways
  - Aero engine failure prediction
    - Public dataset
    - Has been modeled with multi-class classification models
    - RUL-emphasized (Remaining Useable Life Time TTNF Time to the Next Failure)
  - On my PC, thus stand alone Python 3 (DSVM) with keras and cntk
  - On AMLW on my pc with keras and cntk
  - On Azure Databricks with keras & TensorFlow



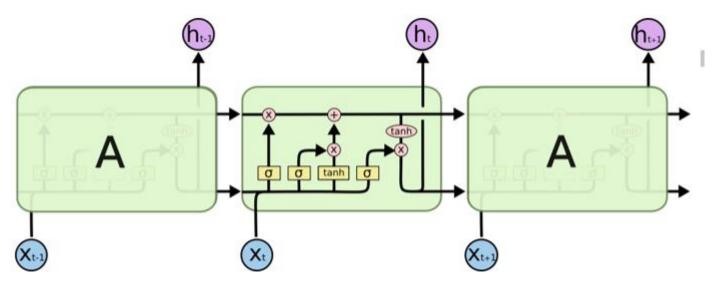
## DNN DevOps Environments

- Software: Python 3
  - DNN framework package: keras.
  - Open source DNN package: TensorFlow, scikit
  - Microsoft DNN package: Cognitive Toolkit CNTK
- Hardware: CPU/GPU or cluster
  - DSVM
  - Machine Learning Workbench
  - Databricks cluster



# Long Short Term Memory Networks

- LSTMs also have this chain like structure, but the repeating module.
- There are four, interacting in a very special way in the repeating module.





The repeating module in an LSTM contains four interacting layers.

### LSTM for Predictive Maintenance

- Dr. F B Uz: <a href="https://azure.microsoft.com/en-us/blog/deep-learning-for-predictive-maintenance/">https://azure.microsoft.com/en-us/blog/deep-learning-for-predictive-maintenance/</a>
- Predictive Maintenance: Data is collected over time to monitor the state of an asset with the goal of finding patterns to predict failures.
- LSTMs are appealing to the predictive maintenance since they are very good at learning from sequences.



# LSTM in Python

```
# huild the LSTM network
nb features = seq array.shape[2]
nb_out = label_array.shape[1]
model = Sequential()
model.add(LSTM(
         input shape=(sequence length, nb features),
         units=100,
         return sequences=True))
model.add(Dropout(0.2))
model.add(LSTM(
          units=50,
          return_sequences=False))
model.add(Dropout(0.2))
model.add(Dense(units=nb_out, activation='sigmoid'))
model.compile(loss='binary_crossentropy', optimizer='adam', metrics=['accuracy'])
```

### Deep Learning is everywhere. Which one is yours?



www.Microsoft.com