

Observations on the Application of Machine Learning Techniques to Aviation Operations

Dr. Banavar Sridhar

Universities Space Research Association (USRA)

@NASA Ames Research Center

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Advances in Machine Learning



Open Source Software



Inadequate Physical Models



What is this talk about?

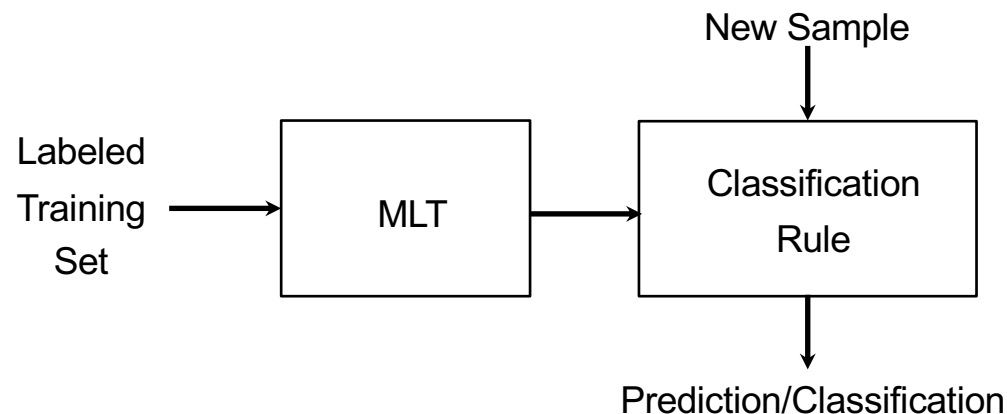
- Increasing interest in applying Machine Learning Techniques (MLT) to solve problems in Aviation Operations (AO)
- Review simulation and analysis methods in AO
- Compare physics-based modeling and data driven Modeling
- Promises and challenges based on applying MLT at NASA
 - Vision-based object detection
 - AO (Controller workload to Route selection decision)
- Concluding remarks

Simulation and Analysis

- Problems in AO range widely in spatio-temporal scale
 - Conflict detection involving two aircraft (local, seconds)
 - Controlling traffic in a sector (many aircraft, minutes)
 - Traffic Flow Management (Large number of aircraft, hours)
 - Impact on climate (Global and several decades)
- Most problems in Air Traffic Management (ATM) can be formulated as
 - Prediction of trajectories
 - Classification of trajectories
 - Optimization of trajectories
- Modeling approach
 - Task, knowledge base, available data

Machine Learning Techniques (MLT)

- Machine Learning: ability to automatically learn to make predictions and classification based on past observations
- Major concepts in MLT originate from Pattern Recognition, Computer Vision, Text Processing and Voice Recognition (sparse or repetitive data)



- MLT frequently used in ATM applications
 - Support Vector Machine (SVM), Decision Trees, Neural Networks, Reinforcement Learning (RL)

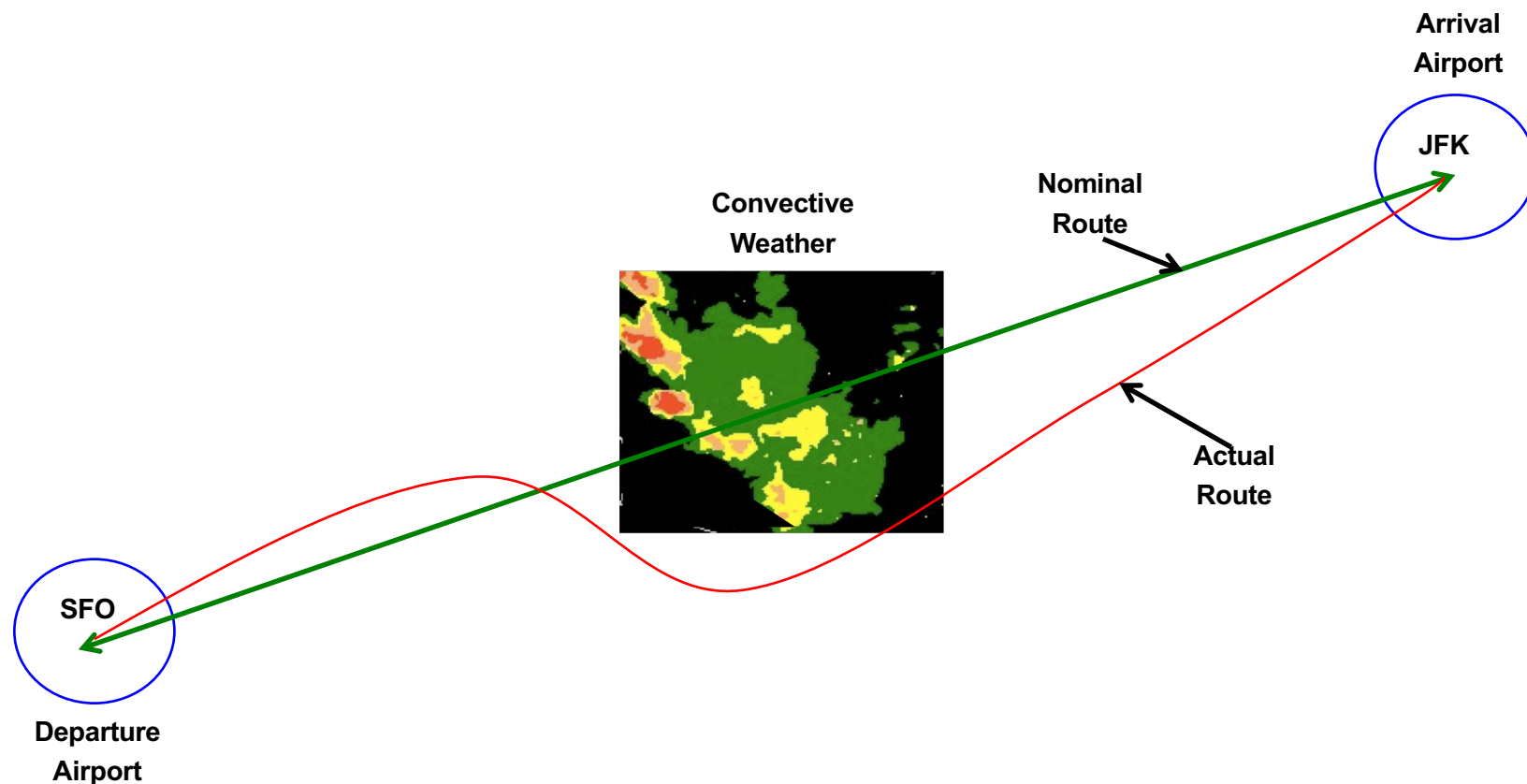
Physics-based and Data-driven Models

Property	Physics-based Models	Data-driven Models
Model	Linear, Non-Linear, Dynamic, Static, Queueing	Black-Box
Interpretation	Easy to explain results in terms of physical quantities	Hard to interpret and gain trust in the system
Model-Building	Expensive and requires lot of application expertise	Availability of quantity and quality of data
Suitability	Availability of well-defined physical models	Ideal for building causal relationship between inputs and outputs when good physics-based models are non-existent or expensive to build
Feature Selection	Defined by the model and various methods to reduce dimensions (Aggregation, time and space separation)	Major issue to reduce the dimension in complex problems
Size	Various methods to determine minimal order unbiased minimal variance models	Efforts to balance over-fitting and under-fitting by cross-validation, regularization and other methods

Challenges in Applying MLT

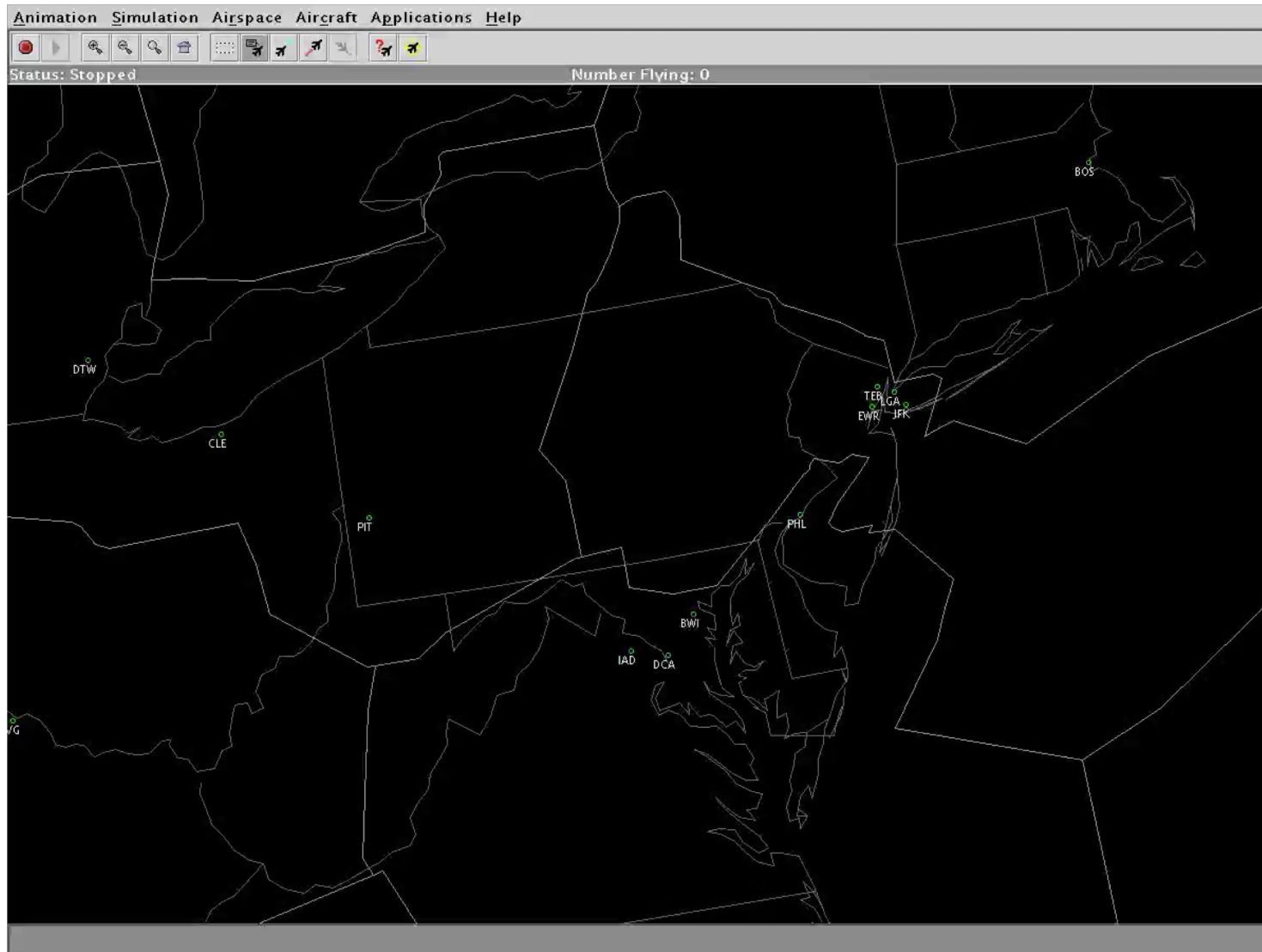
- Availability of training data
 - Security, Regulatory and Proprietary issues
 - Appropriateness of available data to the task
 - Imbalanced datasets
- Feature selection
 - Expert opinion, reduction of problem size
- Selection of a learning method
 - Classification, regression, supervised, unsupervised, accuracy, interpretation of results
 - No single algorithm is best for all tasks
- Balance between overfitting and underfitting
- Performance evaluation
 - 10-fold cross-validation; natural split in data

Task: Model and predict flight delays and cancellations due to weather

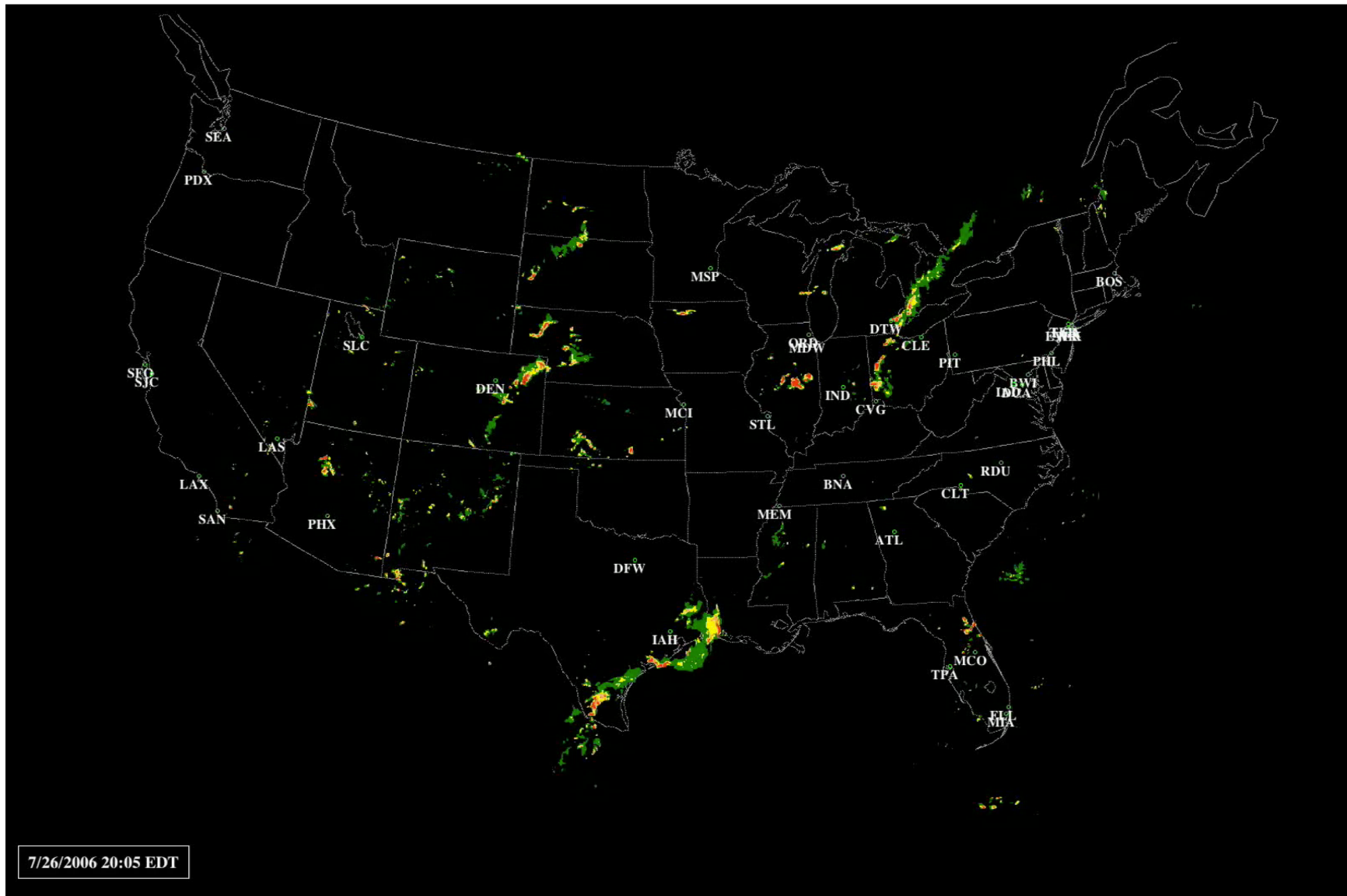


- Weather is the major cause of delay in the National Airspace System (NAS)
- Relate delay, cancellations and other NAS performance metrics to the weather conditions

Traffic and Weather

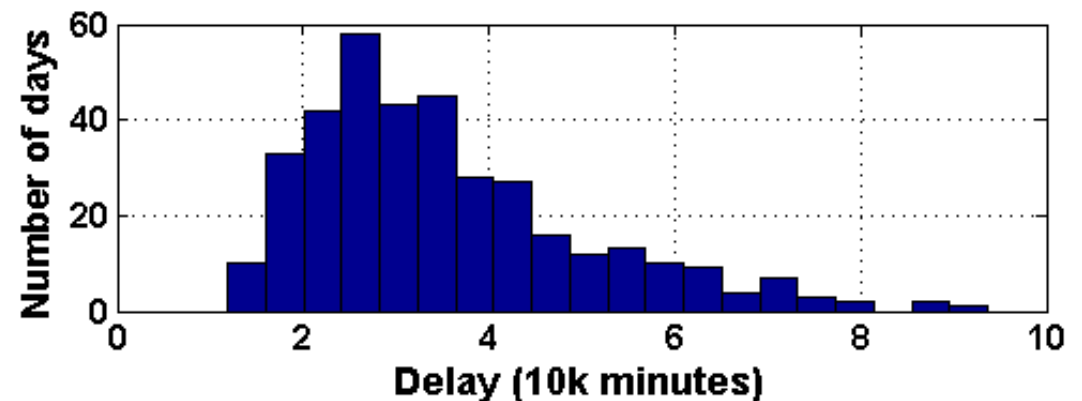
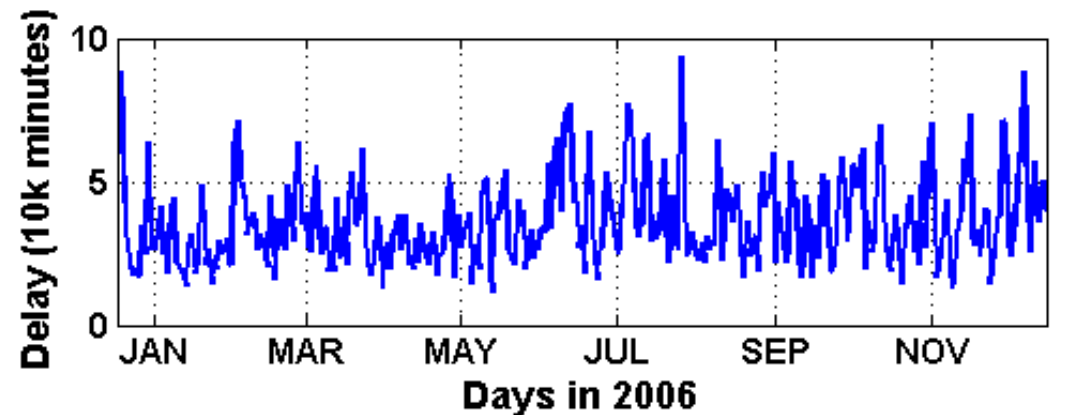


Flight Delays



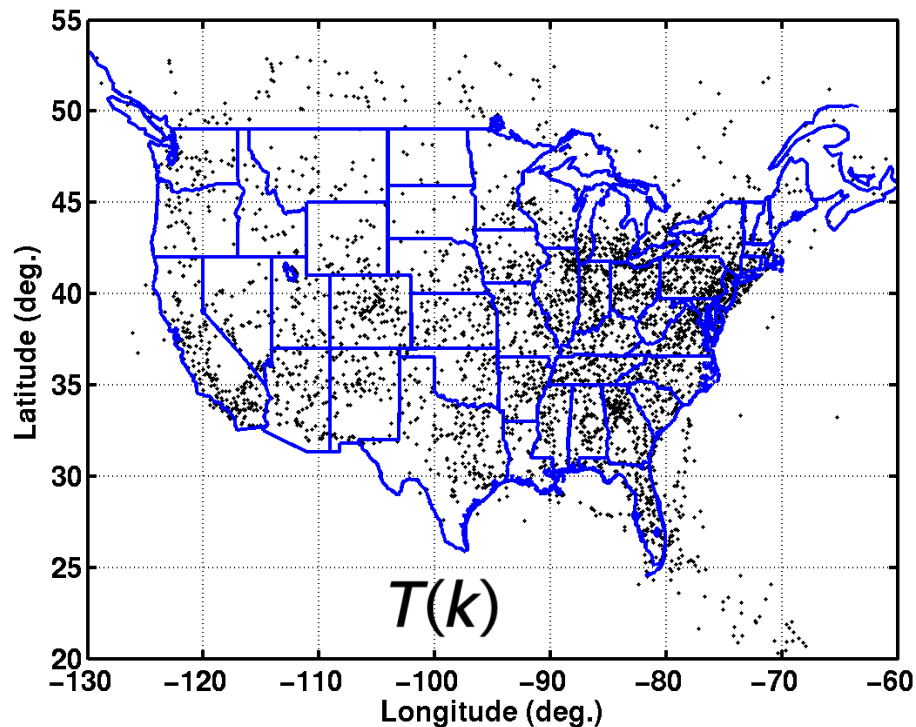
Factors in modeling delay

- Data
 - Operations Network (OPSNET), Aviation System Performance Metrics (ASPM)
 - Traffic Data (2004-2008)
 - Convective Weather, Wind data
- Choice of nominal traffic
- Feature selection
- Modeling approach

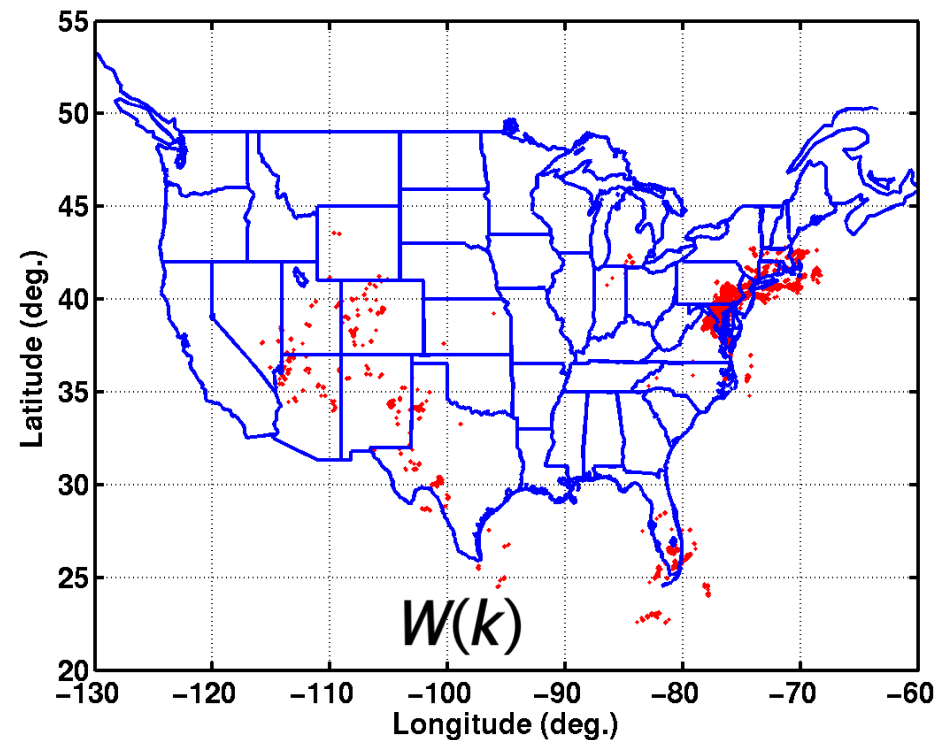


Feature Selection : Weather Impacted Traffic Index (WITI)

Aircraft positions



Severe weather

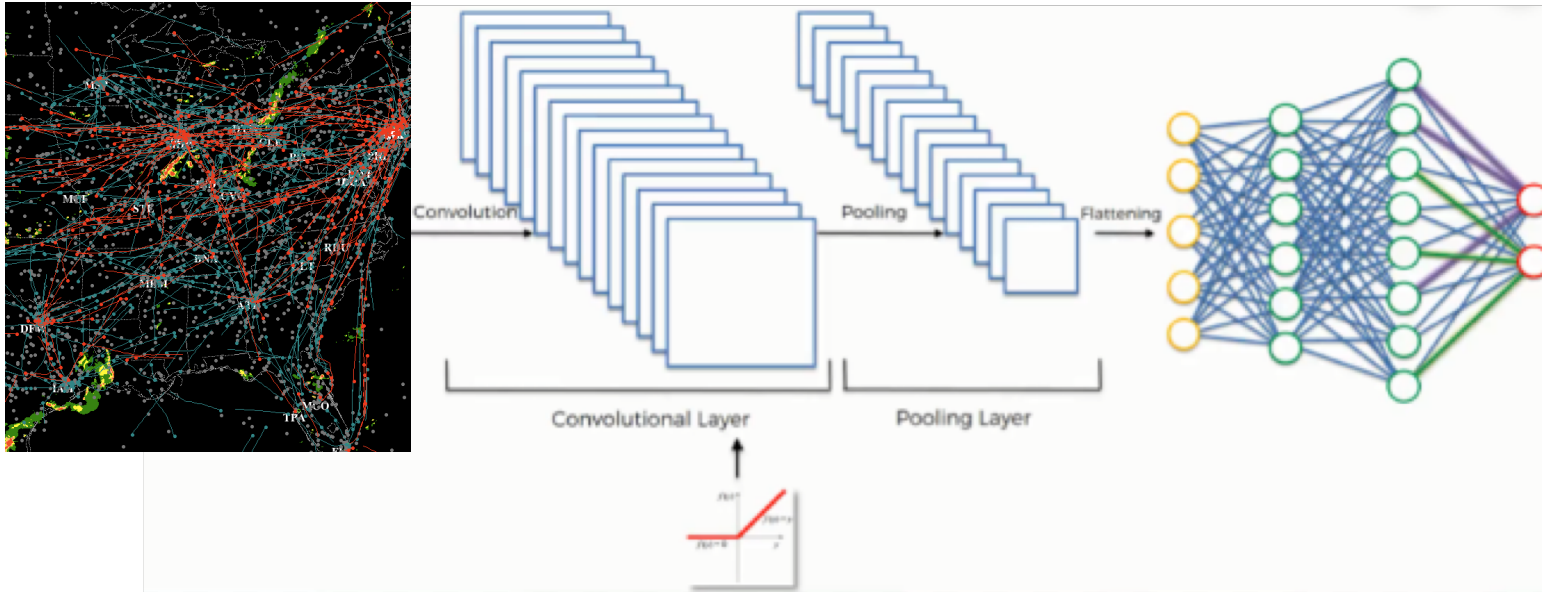


$$WITI(k) = \sum_{1 \leq j \leq m} \sum_{1 \leq i \leq n} T_{i,j}(k) W_{i,j}(k)$$

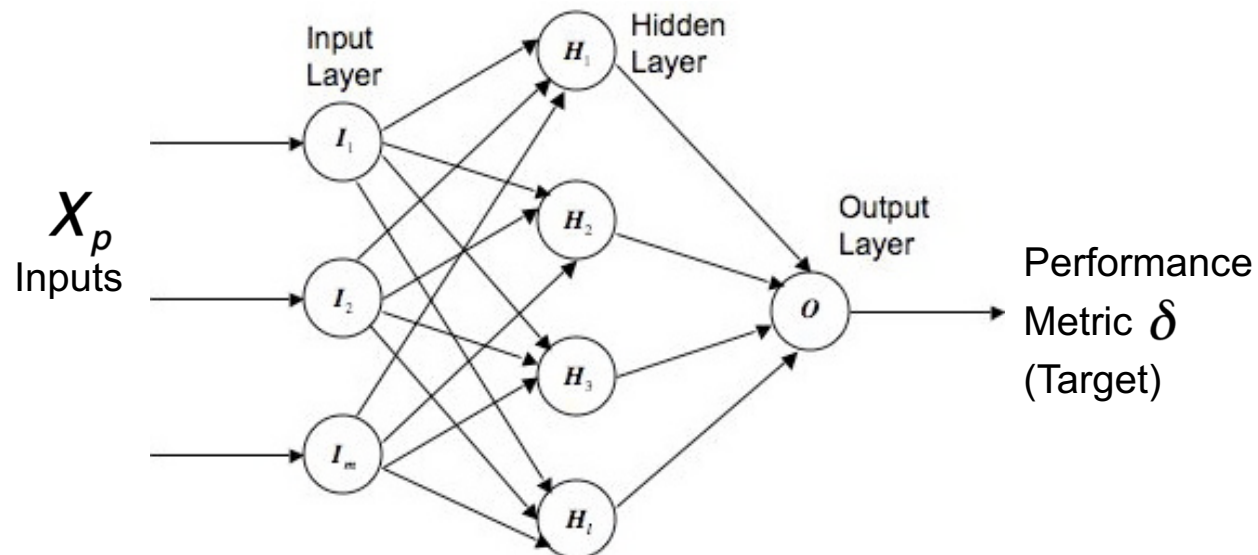
Modeling approach

- Number of aircraft affected by weather (X)
- Number of aircraft affected by weather in each Center or airport (X_p)
- Performance metric: Delay or Cancellation δ
- Linear Regression (LR): $\delta = \alpha X + \beta$
- Multiple Linear Regression (MLR): $\delta = \sum_{p=1}^{20} \alpha_p X_p + \beta$
- Neural Networks: $\delta = f(X_p, NW)$

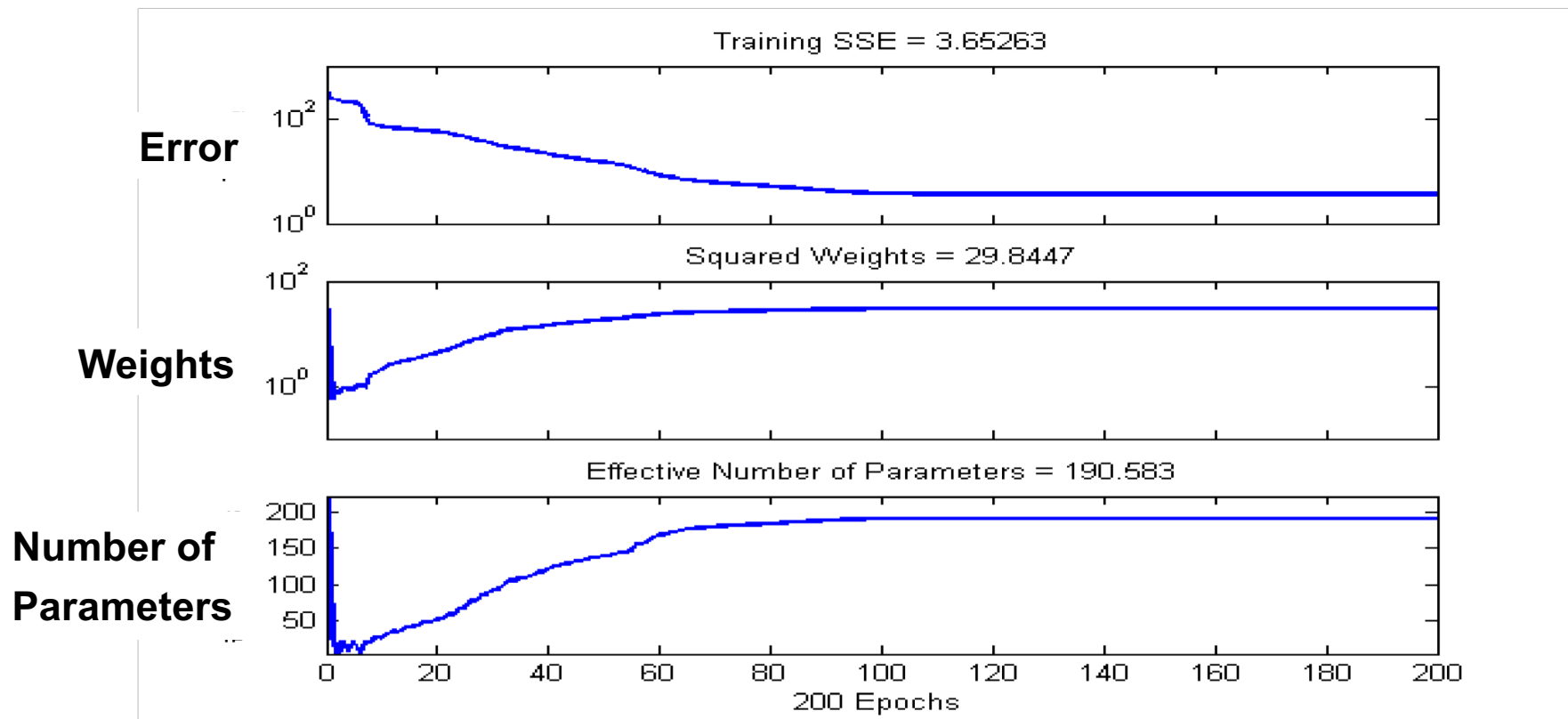
Neural Networks



- Selection of WITI reduces the input images of traffic and convective weather and simplifies the convolutional and pooling layers



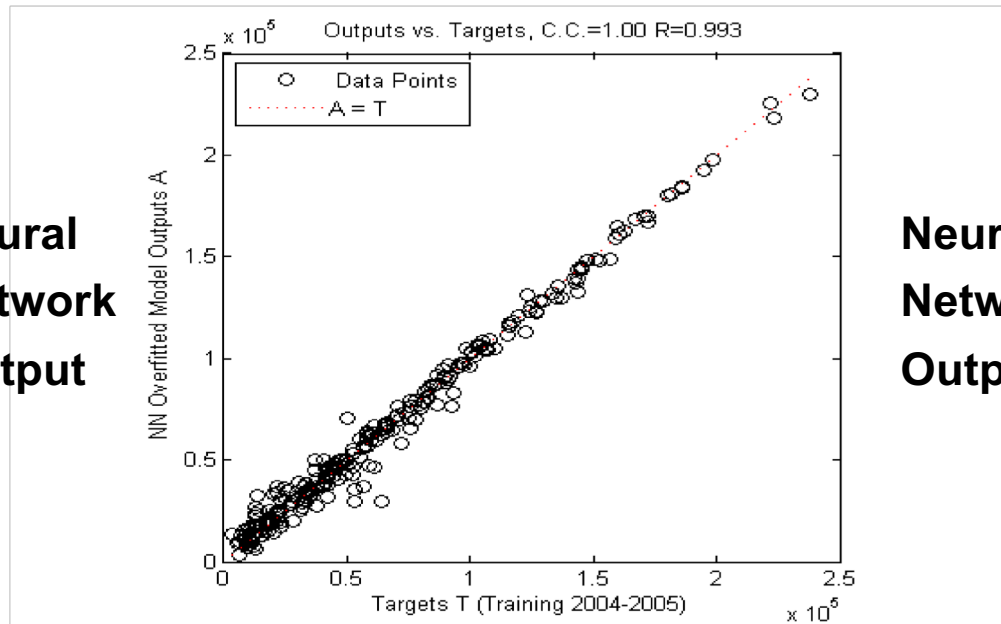
Variation of Training Error



- Result of training after 200 epochs
- Neural network represents total delay training data extremely well

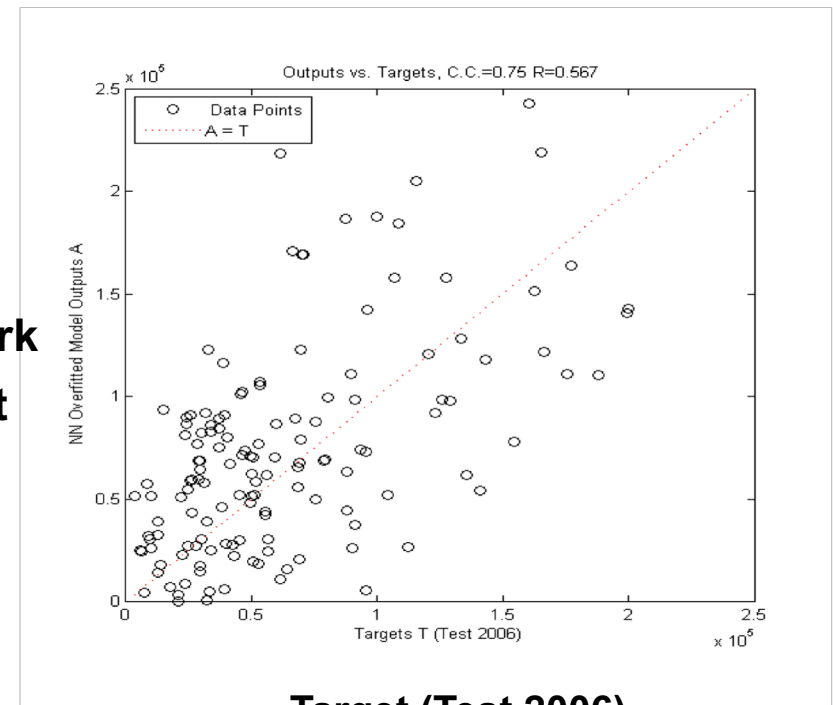
Over fitted Neural Network

**Neural
Network
Output**



Target (Training 2004-2005)

**Neural
Network
Output**

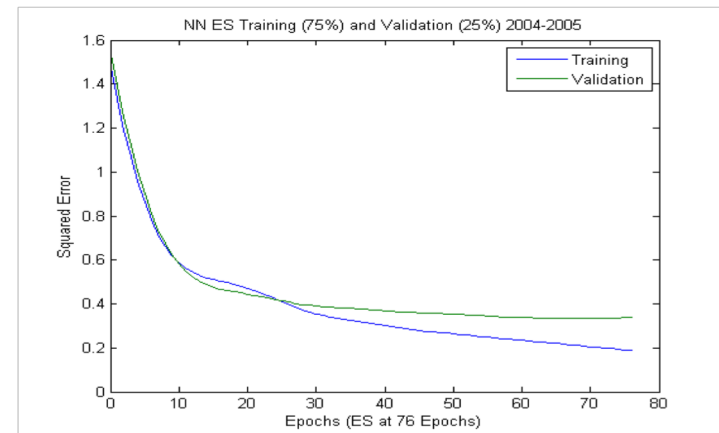


Target (Test 2006)

- Model fits the total delay training data (2004-2005) well, but does not generalize (correlation coefficient for test set is significantly less)

Methods for Good Design

- Training data should be sufficiently large and statistically representative
- Overly complex models should be avoided
- Methods to reduce complexity
 - Early Stopping (ES), Principal Component Analysis (PCA), Stepwise Regression (SR), Bayesian Regularization (BR)
- Early Stopping
 - Stop training if there is no improvement in the accuracy of test data
 - N-fold cross-validation



Computational Results

OPSNET total delay

Method	CC	RMSE	MAE
LR	0.71	32700	26600
MLR	0.77	31200	24500
BR	0.88	30000	23000
ES	0.88	30900	23200
PCA	0.88	30100	23100
SR	0.88	29600	22300

ASPM Scheduled delay

Method	CC	RMSE	MAE
LR	0.75	99200	74300
MLR	0.76	97600	72900
BR	0.88	95800	74300
ES	0.88	94200	70800
PCA	0.88	91700	68600
SR	0.87	99100	73800

Five-fold cross-validation

Method	CC	RMSE	MAE
BR	0.88	29100	22000
ES	0.88	31500	23900
PCA	0.87	30500	23300
SR	0.89	29600	22500

Five-fold cross-validation

Method	CC	RMSE	MAE
BR	0.87	93700	70300
ES	0.87	95000	72000
PCA	0.87	94900	70800
SR	0.85	96100	73000

Correlation Coefficient (CC), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE)
Neural Network methods to reduce complexity: BR,ES,PCA,SR

Traffic Delay Estimation

Problem	Flight Delay and Cancellation in US
Data	FAA OPSNET and ASPM data Convective weather 2005-2008.
Method	MLR and feed-forward NN with several stopping criterion
Feature Selection	Weather Influenced Traffic Index(WITI) at the Center, National and airport level
Method of Evaluation	MAE, RMSE and Correlation Coefficient
Remarks	For all metrics and seasons at all levels NN produced slightly better results the MLR

Applications from literature

Application	Data	MLT	Remarks
NAS Performance Metrics	OPSNET, ASPM Convective Weather (2005-2008)	LR,MLR, FFNN	FFNN performed better than MLR
	BTS data (2011-12) Hourly delays 1107 O-D pairs between 14 airports	MJLS, CART, NN	NN and MLJS performance varied with task
Anomaly Detection	Boeing 777 aircraft data 365 flights between 14 airports	Density based clustering algorithm	Identified outliers during take-off and landing Poor sensitivity to short duration anomaly
Conflict detection And resolution	Mode-S data covering France 21314 aircraft trajectories with 8 parameters (position, speed,...)	MLR, SVM, FFNN GBM, RF	MLT performed better than baseline; GBM performed best
	Randomly generated conflict data 15 aircraft in 100nm diameter circle	RL	RL identified 81% of the conflicts under uncertainty
ATC decision Making	Accepted/rejected DWR test data at American Airlines May-September 2014	Logistic Regression SVM, CART, RF Adaboost	RF and Adaboost performed best
	8760 Hourly observations during 2012 LAMP, GDP, NTML, RUC, ASPM	Logistic Regression Decision Trees	MLT identified different types of weather days similar GDP days

Concluding Remarks

- MLT provides a new class of tools
 - Method of choice in the absence of physics-based models
 - No single ML algorithm is best for all applications
 - Feature selection plays a key role
- More research needed on performance evaluation of MLT for critical tasks
- Task, prior knowledge, data: key to modeling approach

Who is your most famous
data scientist?