Decision Support Tool for Predicting Aircraft Arrival Rates from Forecast Weather Data

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CENTER FOR AIR TRANSPORTATION SYSTEMS RESEARCH

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Agenda

1. Introduction
    - Problem
    - Scope
    - Objectives
    - Contribution
2. Review of Prior Research
3. Methodology
4. Comparison of Alternate Methods
5. Operational Results
6. Delay Tool Strategies
7. Conclusions

Problem

- Air traffic congestion is a widespread phenomenon within the US
- Bottleneck of the NAS is at the airports
  - Arrival demand exceeds capacity at peak hours
  - Increasing arrival slots is not an option
  - Resulting delays (airborne or ground)

Scope

- Efficiency is defined as maximizing all available airplane landing capacity at an airport
- Capacity is measured by aircraft arrival rates (AAR)
- When the weather deteriorates, controllers increase the separation between aircraft (decrease the AAR)
- When the system is congested, the FAA slows down the flow of arrivals into an affected airport by imposing a Ground Delay Program (GDP) at appropriate departure airport

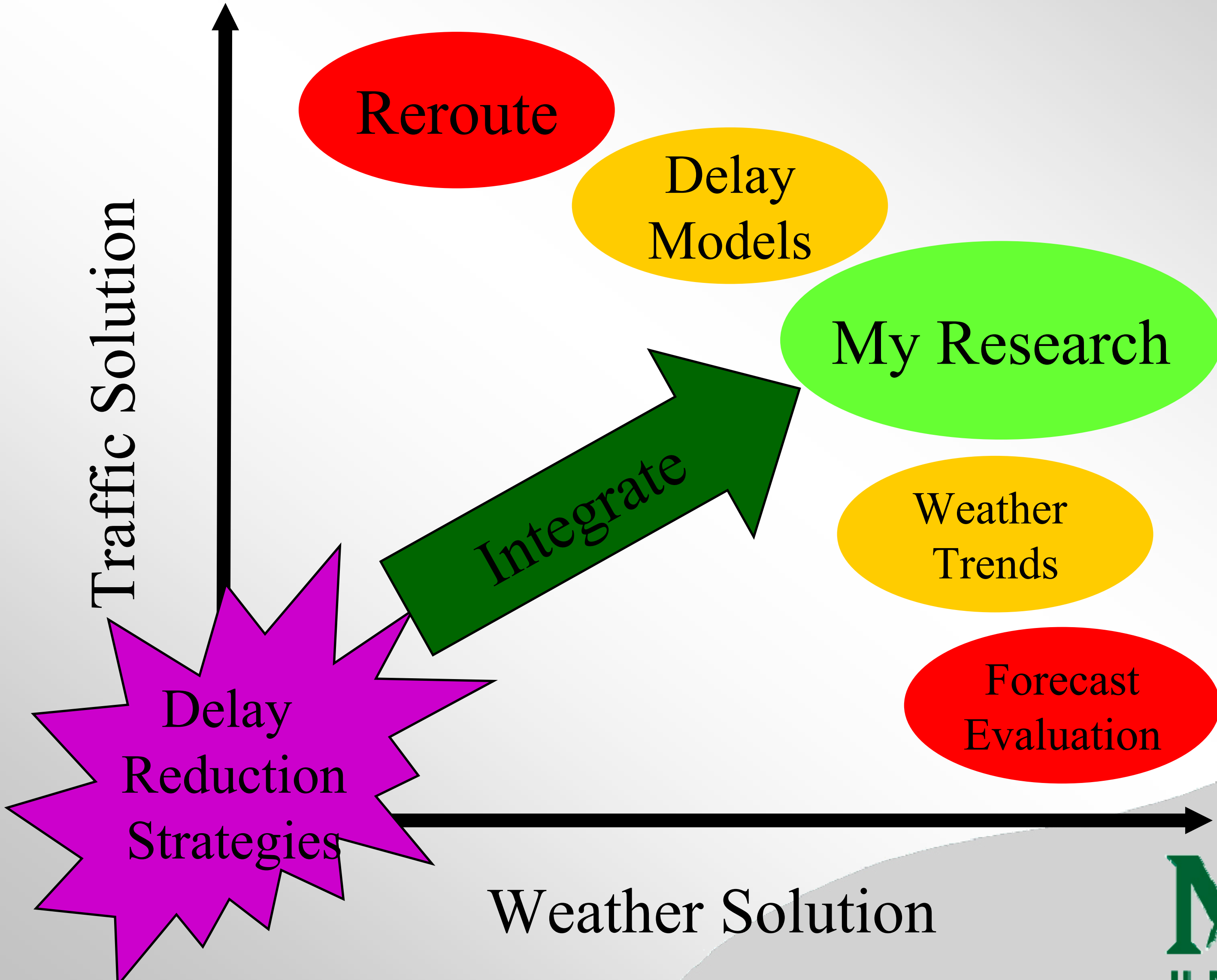
Solutions

- Intent is NOT to increase airport capacity
- Provide an improved network planning framework
- Better proactive plan to major network perturbations
- Predict when AAR will be decreased
- Present solutions to alleviate excess demand
- Emphasis on major hub airports because of the amplified effect on the overall network delay performance

Benefits of Research

- For the Air Traffic Control System Command Center (ATCSCC), adapting the Military Decision Making Process to air traffic management will produce a systematic and consistent procedure for planning an operational day in the NAS
- Both the ATCSCC and the airlines can use a tool that inputs the current Terminal Aerodrome Forecast (TAF) and produces airport capacity predictions hours in advance
- Increase the available planning time to create an evaluate potential courses of action (branch plans)
- Gives insight to how controllers react to forecasts and can further be used in simulations that require operational effects of weather

Method Summary



Intelligence

- What is the enemy to traffic flow?
  - Bad weather
  - Scheduled congestion
- Simulation techniques can be used to predict congestion
- Weather
  - Stochastic
  - Forecasts
    - Time
    - Chance
- Forecast gives us a decision point – time and place
- Create a branch plan?
  - Predict effect on operations – GDP, AAR ect.
  - Formulate a plan to counter the effects
- Solution – use Terminal Aerodrome Forecast (TAF) to predict effect on operations

What is the TAF?

- TAF = Intelligence
- TAF - a concise statement of the expected meteorological conditions at an airport during a specified period (usually 24 hours)
- A TAF report contains the following sequence of elements in the following order:
  - Type of Report
  - ICAO Station Identifier
  - Date and Time of Origin
  - Valid Period Date and Time
  - Forecast Meteorological Conditions
  - Written in TAF "code"
- Produced at least every 6 hours

TAF Example

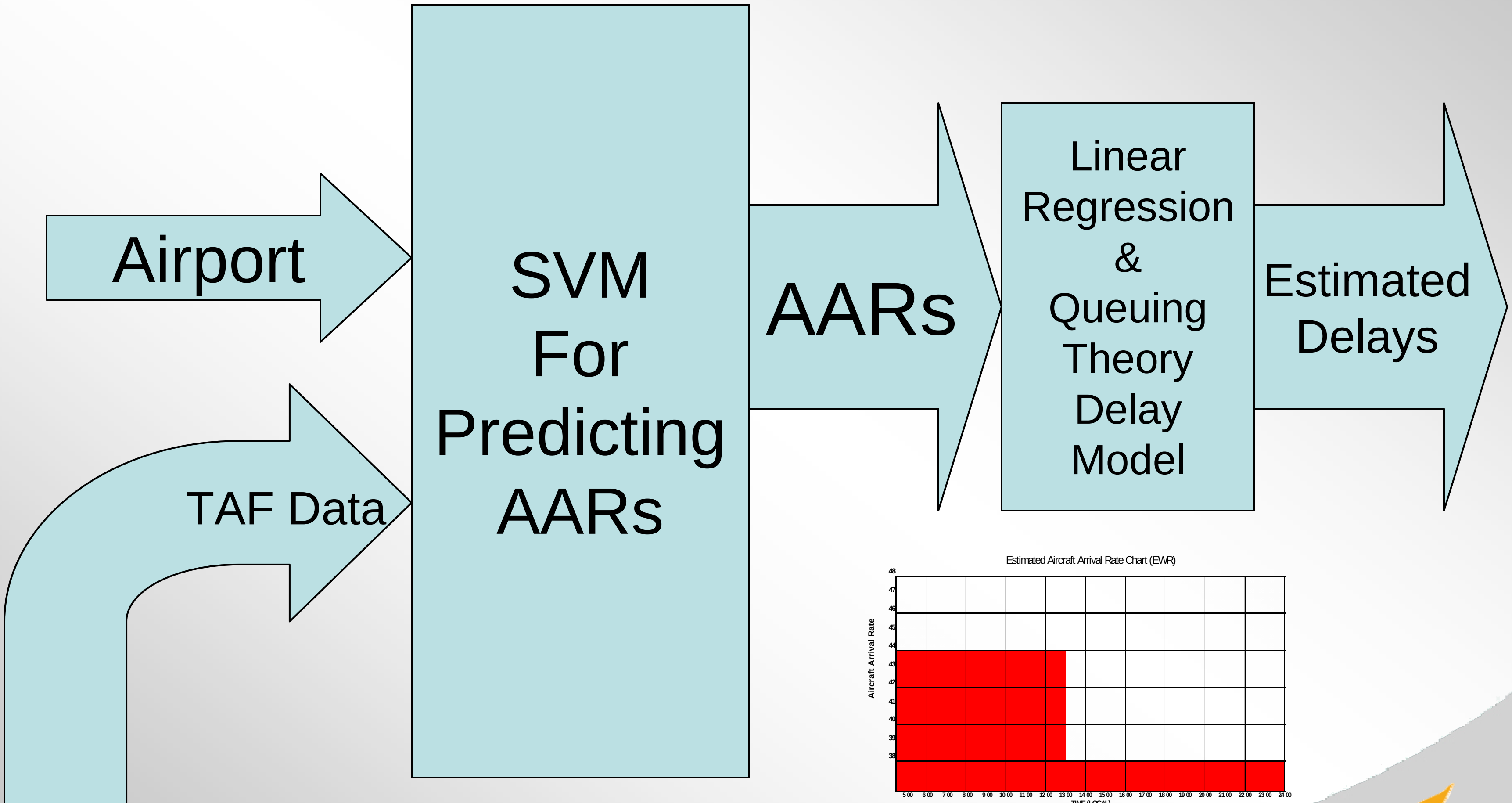
TAF KEWR 161732Z 161818 24017G27KT P6SM SCT040 BKN250
FM1930 29018G32KT 4SM TSRA BR BKN040CB
FM2200 22009KT 6SM SHRA BR OVC040CB
FM0400 33006KT 6SM -SHRA BR OVC040
FM0800 34006KT 6SM BR OVC040
FM1400 26005KT P6SM BKN040

To a computer this is a vector!

Decision Support Tool

- Use TAF to predict
  - Aircraft Arrival Rates
  - GDPs
  - Delays
- GDPs are determined based on AAR rates at specific time during the day
- Delays are estimated based on the AARs and the demand
- Traffic flow managers develop a plan based on the prediction

Method Summary



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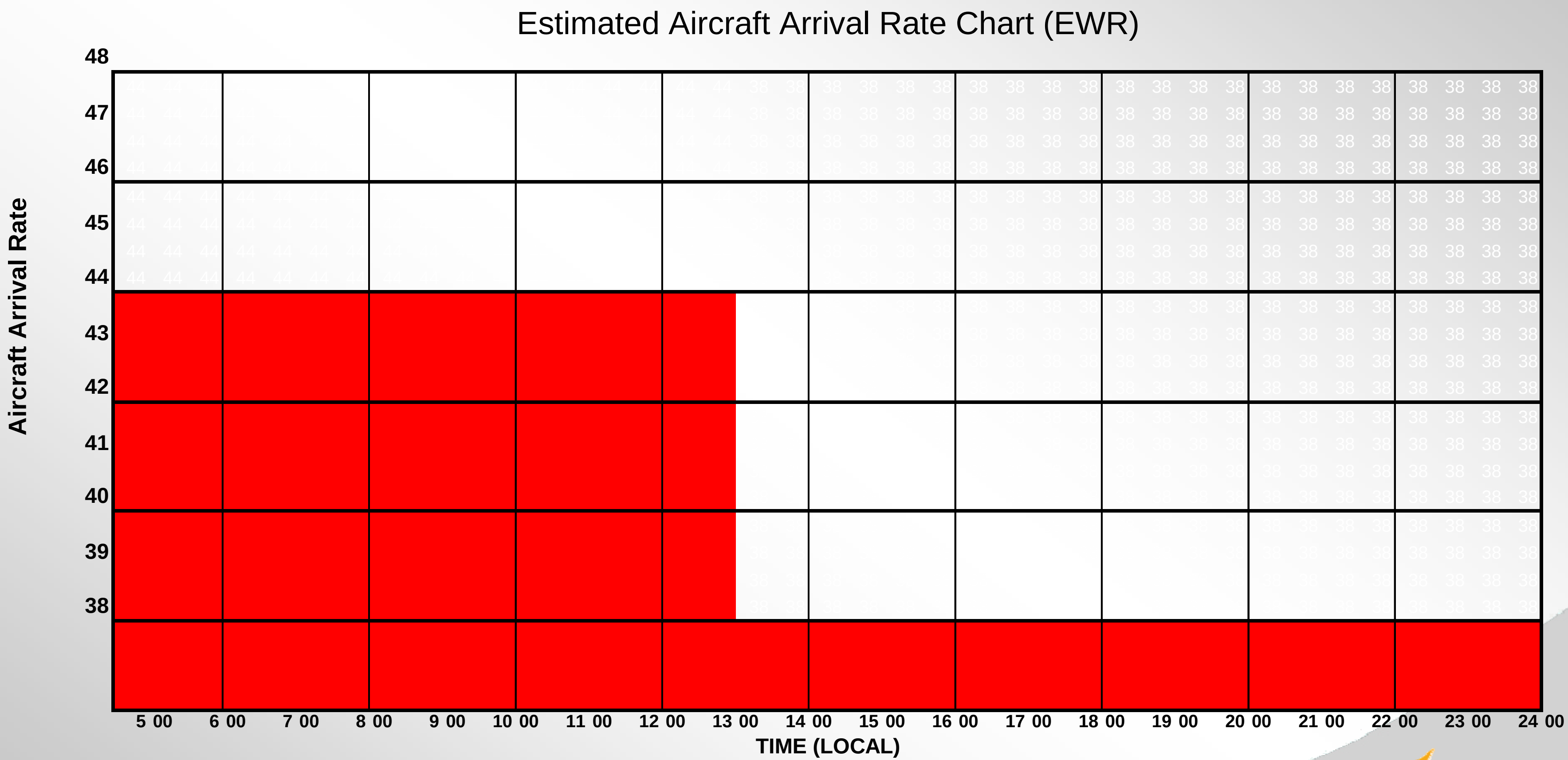
Estimated AAR Chart



Method

1. Convert TAF format to a vector data set
2. Use a pattern recognition tool called the support vector machine (SVM)
3. SVM is trained with past data ('02-'06)
4. Develop functions to present day data to predict outcomes

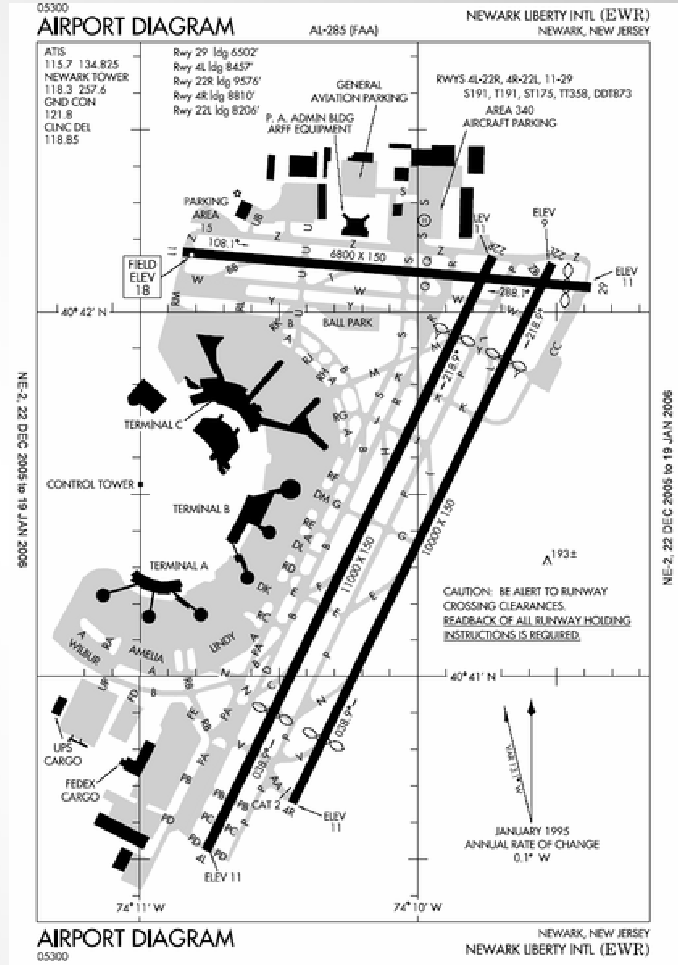
Extracted Data

- Time periods
  - 1100 Zulu
  - 1500 Zulu
  - 1900 Zulu
  - 2300 Zulu
- Wind speed
- Visibility
- Ceiling
  - Overcast
  - Scattered
  - Broken
  - Few
- **Cross Wind**

- Binary variables
  - Rain
  - Snow
  - Showers
  - Thunderstorms
  - Fog
  - Mist
  - Freezing

Crosswind

- Newark Airport
- Primary 4 – 22 R/L
- Crosswind runway 29/11
- Direction and wind is the deciding factor
- Assumed crosswind anywhere between 270 and 350 and between 170 and 90
- Example – Boeing aircraft have a maximum crosswind landing constraint less than or equal to 25 kts



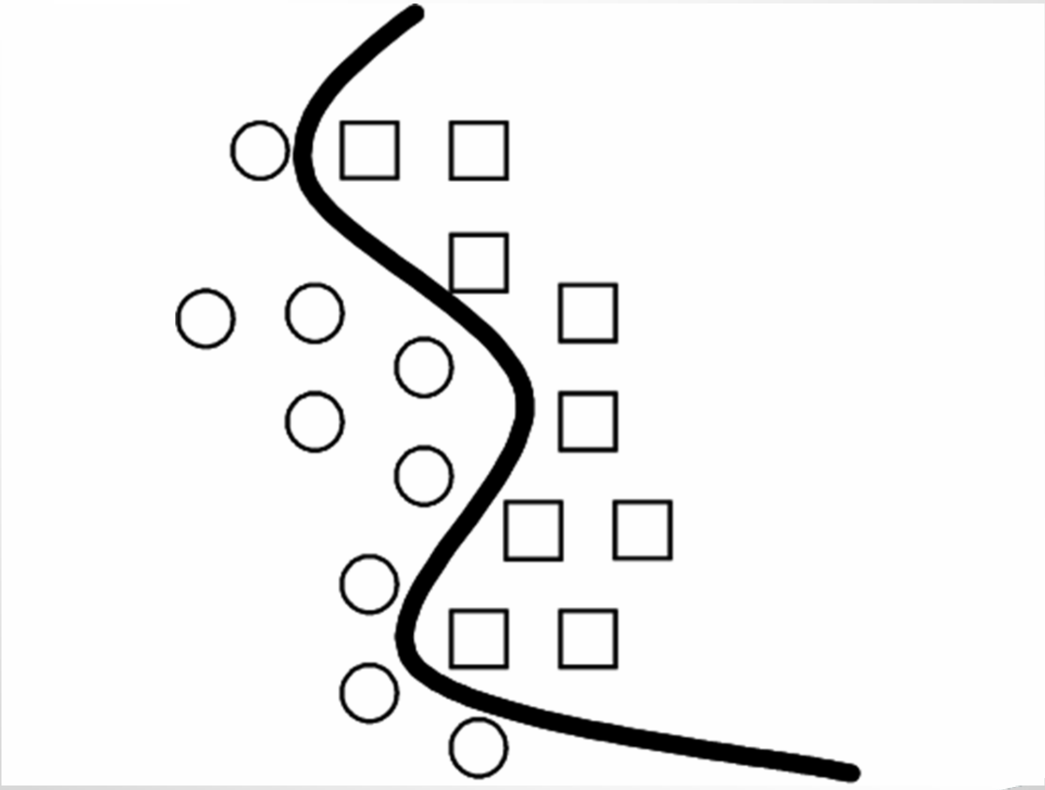
Vector Data Set

Date	Wind Speed	Visibility (mi)	Rain (Y/N)	Snow (Y/N)	Showers (Y/N)	Thunder storms (Y/N)	Fog (Y/N)	Mist (Y/N)	Freezing (Y/N)	Overcast Ceiling	Scattered Ceiling	Broken Ceiling	Few Ceiling	Cross Winds
1	7	6	0	0	0	0	0	0	0				150	0
2	12	6	0	0	0	0	0	0	0		250			0
3	6	6	0	0	0	0	0	0	0			150		0
4	5	5	0	0	0	0	0	0	0			120	60	0
5	6	4	1	0	1	0	0	1	0			60		0
6	8	6	0	0	1	0	0	0	0	60	25	35		0
7	9	6	0	0	0	0	0	0	0		90			1
8	5	6	0	0	0	0	0	0	0			250		0
9	5	6	0	0	0	0	0	0	0		120	250		0
10	6	6	0	0	0	0	0	0	0		100	250		0
11	10	6	0	0	0	0	0	1	0					0
12	6	4	0	0	0	0	0	0	0		15			0
13	11	6	0	0	0	0	0	0	0		50	80		1
14	4	6	0	0	0	0	0	0	0					0
15	3	6	0	0	0	0	0	1	0			250		0
16	4	6	0	0	0	0	0	0	0					0
17	4	6	0	0	0	0	0	0	0					1
18	7	6	0	0	0	0	0	0	0		250			0
19	6	6	0	0	0	0	0	0	0		40	100		0
20	10	6	0	0	0	0	0	1	0			20		0
21	5	5	0	0	0	0	0	1	0					0
22	8	2	0	0	0	0	0	1	0			15		0
23	12	6	0	0	0	0	0	1	0		25			0
24	5	6	0	0	0	0	0	0	0					1
25	6	6	0	0	0	0	0	0	0		250			0
26	5	6	0	0	0	0	0	0	0			250		0
27	7	6	0	0	0	0	0	0	0		250			0
28	6	6	0	0	0	0	0	0	0			90	5	0
29	8	6	0	0	0	0	0	0	0					1
30	4	6	0	0	0	0	0	0	0		50	100		1
31	7	6	0	0	0	0	0	0	0		250			0

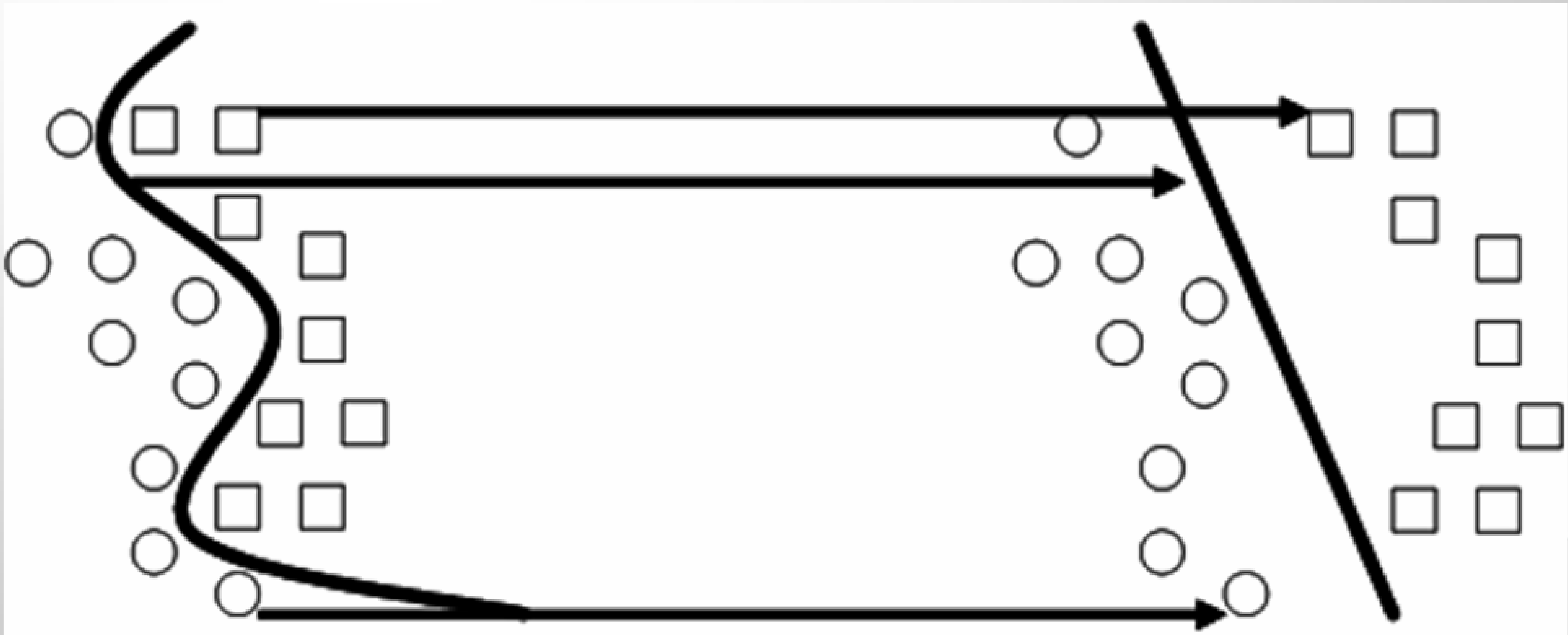
Support Vector Machine

- Supervised learning method
- Generates input-output mapping functions from training data
- Decision plane separates between a set of objects having different class membership

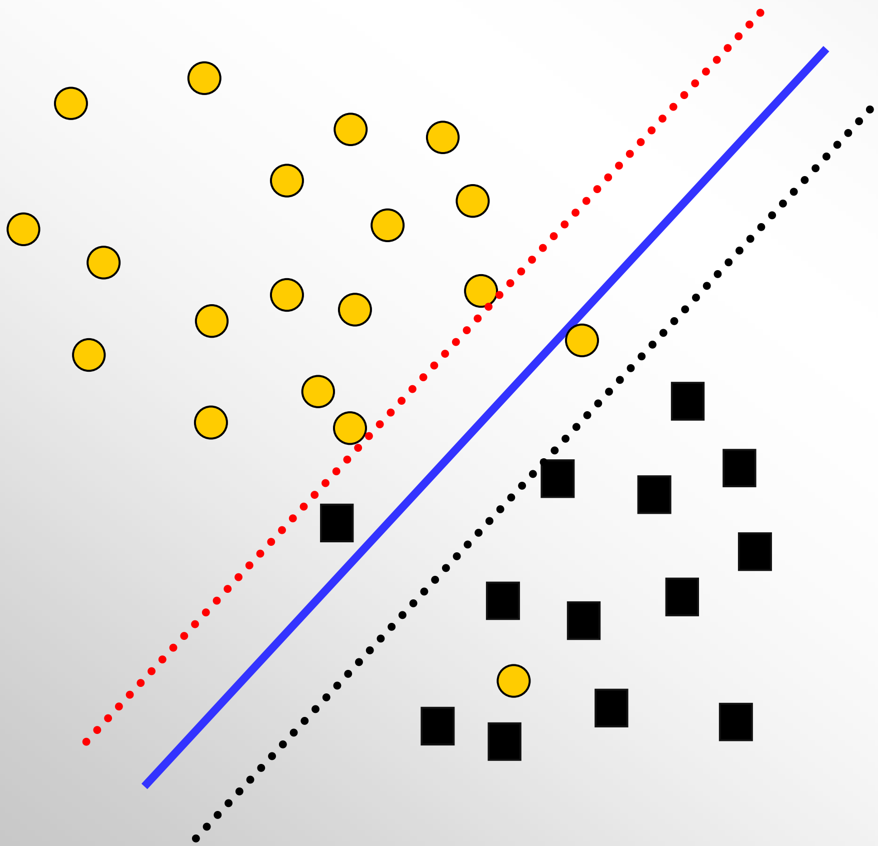
Graphic Example



Example (cont.)



Linearly Inseparable Case: Supporting Plane Method



$$\min_{w,b,z} \quad \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{N} z_i$$

$$s.t. \quad y_i\left(x_i^T w + b\right) + z_i \geq 1$$

$$z_i \geq 0 \quad i = 1,..,l$$

Data Collection

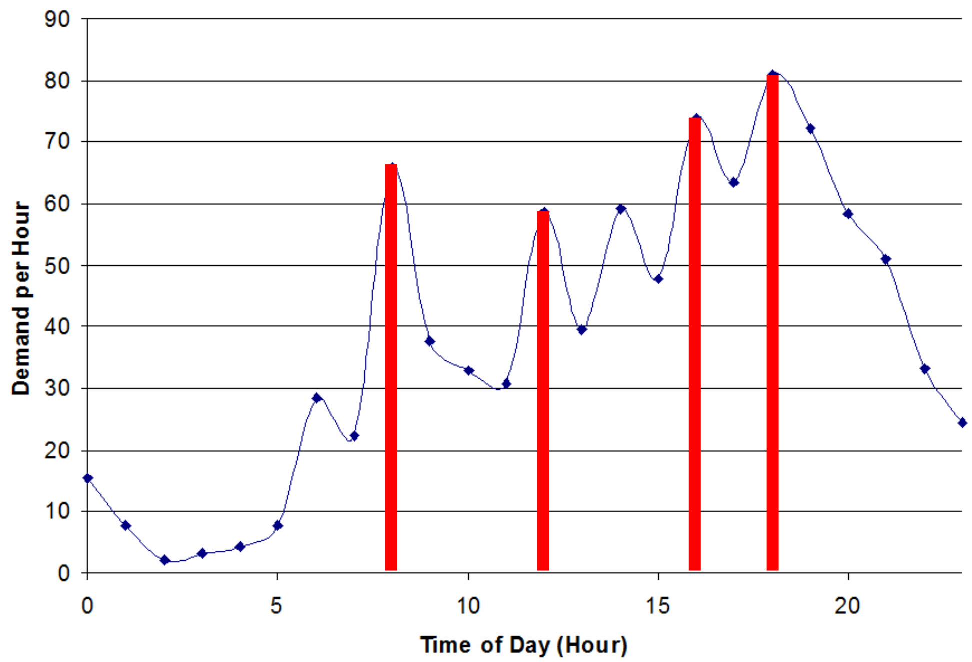
- TAF Data from National Climatic Data Center
  - Use Excel macro to convert to linear data
  - Used data from 2002 and 2006
- Bureau of Transportation Statistics
- Airline System Performance Metrics (ASPM)
- Airports
  - Newark (EWR)
  - O'Hare (ORD)
  - Atlanta (ATL)
  - Philadelphia (PHL)
  - LaGuardia (LGA)
  - New York - Kennedy (JFK)
  - Reagan National (DCA)
  - Dulles (IAD)

Predicting AAR

- Collect TAF data as the independent variable
- Quadratic program loaded into AMPL
- TAF data is transformed into the integer vector x
- AAR indicator variable y
  - -1 indicates negative test
  - 1 indicates positive test
- Program output
  - Solution w vector
  - Linear y-intercept vector b
- Prediction equation $w_i^T x_i + b$

PHL Example

- Philadelphia is a "pacing" airport (FAA 2006)
- Determine peak hours based on demand
  - Average demand for 2002 through 2006
  - Peak hour are used to choose time period to analyze
- Group the AARs based on a common set



- Chose 4 of the six peaks
  - 0800
  - 1200
  - 1600
  - 1800
- Common AARs
  - 52
  - 48
  - 36

Predicting AAR

- Determine 8 SVM prediction functions
  - Test 2 AAR divider points
  - 4 time periods
- SVM runs determine whether or not there will be an AAR less than *x*
- Use predictor function to predict future days
  - If less than 48, then 36
  - else If less than 52, then 48
  - else 52

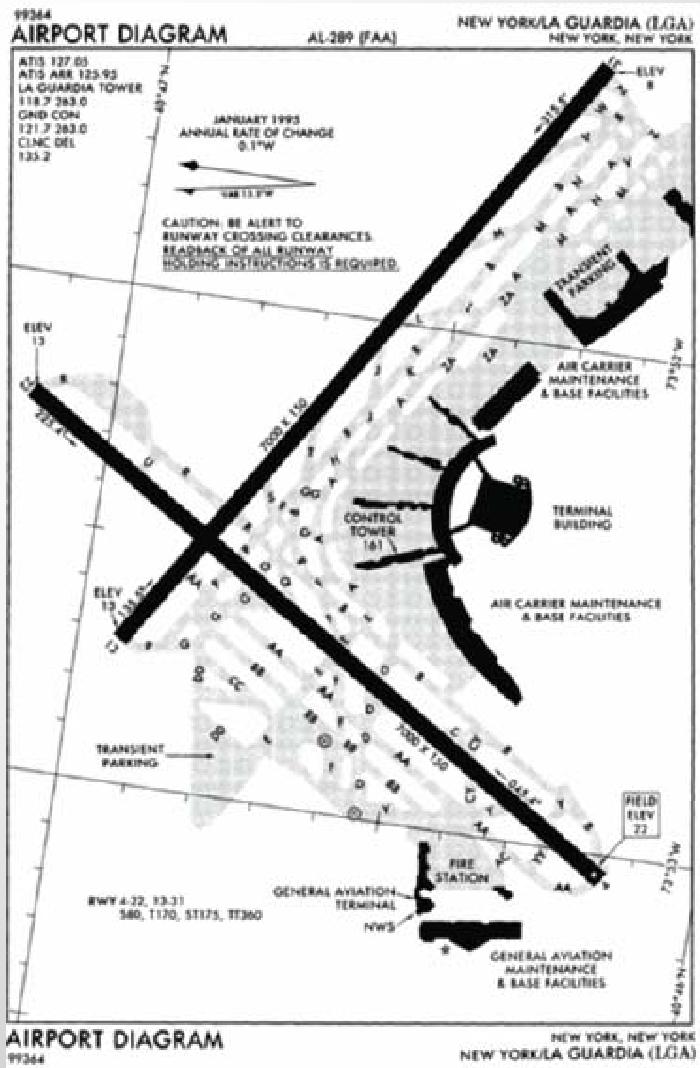
PHL Training Data
(Jan 2002 – Dec 2006)

Time	AAR	% of Predictions Correct	% of Actual AAR Occurrence
800	36	72%	12%
	48	41%	18%
	52	78%	70%
1200	36	64%	9%
	48	46%	17%
	52	74%	74%
1600	36	75%	6%
	48	40%	18%
	52	76%	76%
1800	36	75%	6%
	48	39%	18%
	52	75%	76%

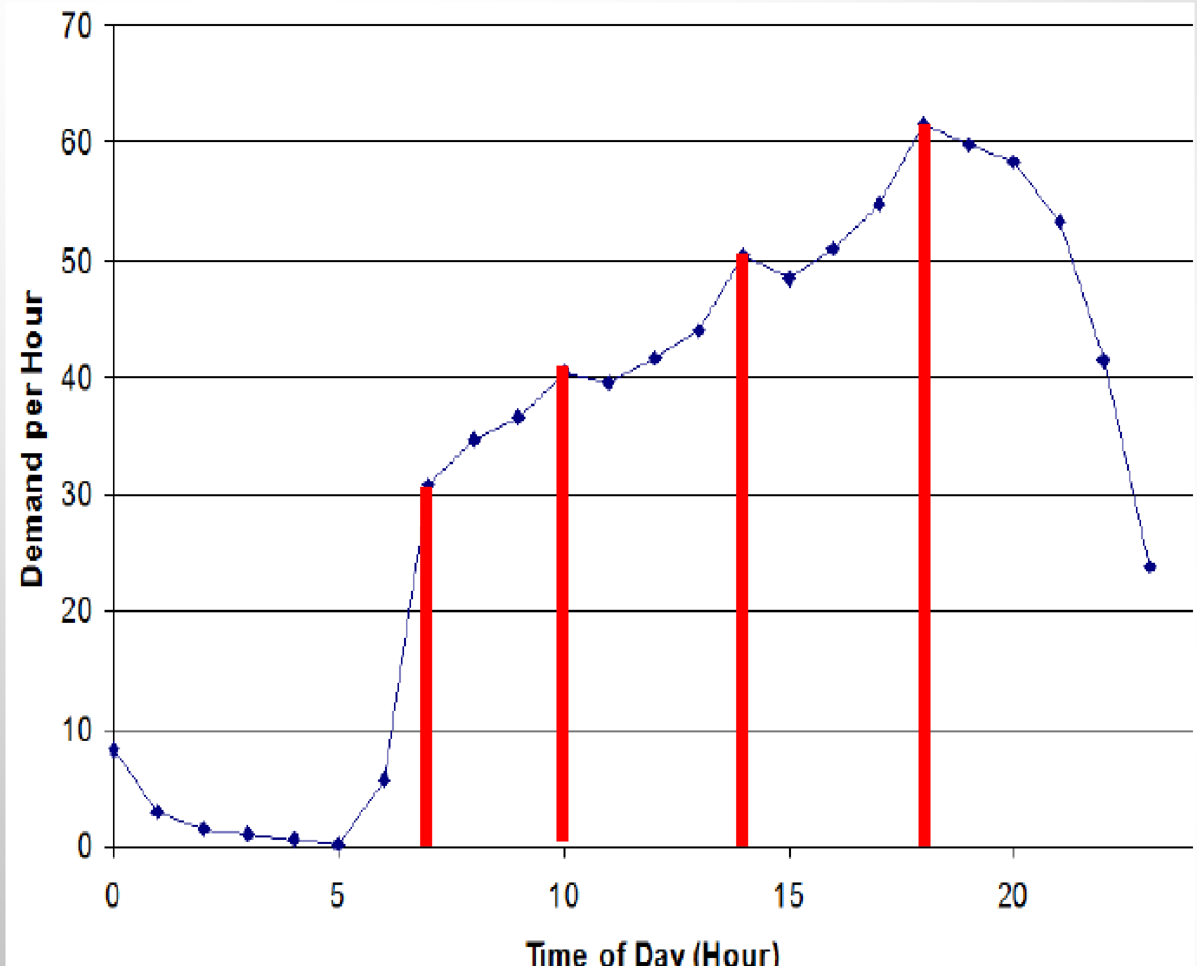
PHL Testing Data
(Jan 2007 – Jun 2007)

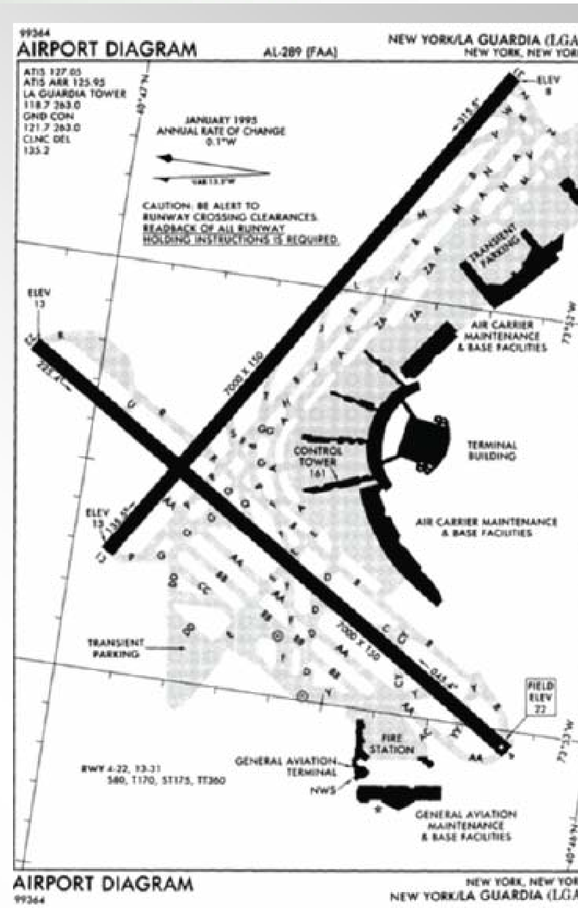
Time	AAR	% of Predictions Correct	% of Actual AAR Occurrence
800	36	76%	14%
	48	25%	7%
	52	79%	80%
1200	36	92%	7%
	48	30%	11%
	52	77%	82%
1600	36	77%	7%
	48	29%	9%
	52	83%	84%
1800	36	73%	6%
	48	28%	10%
	52	81%	84%

LaGuardia Results

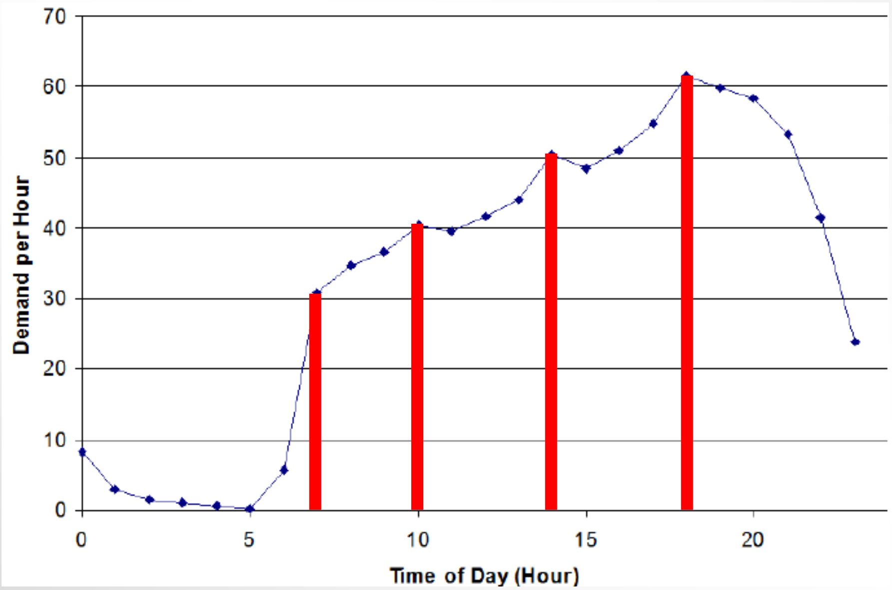


LaGuardia Results



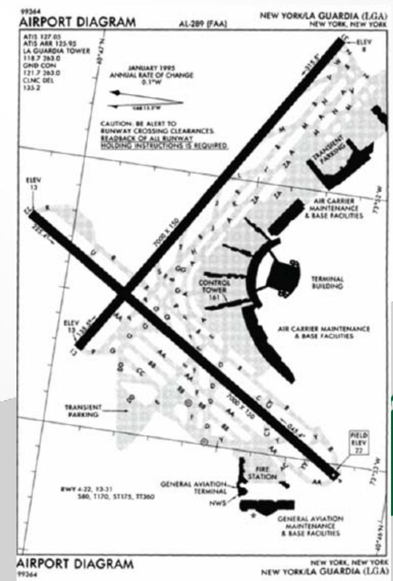


LaGuardia Results



LGA Training Data 2002-2006			
Time	AAR	% of Predictions Correct	% of Actual AAR Occurrence
700	32	66%	20%
	37	39%	57%
	40	73%	23%
1000	32	64%	26%
	37	38%	50%
	40	71%	24%
1400	32	67%	21%
	37	34%	64%
	40	68%	15%
1800	32	67%	15%
	37	31%	80%
	40	73%	5%

LGA Testing Data Jan-Jun 2007			
Time	AAR	% of Predictions Correct	% of Actual AAR Occurrence
700	32	43%	4%
	37	29%	4%
	40	33%	92%
1000	32	67%	5%
	37	33%	3%
	40	30%	92%
1400	32	75%	7%
	37	33%	22%
	40	27%	71%
1800	32	64%	8%
	37	49%	65%
	40	46%	28%



Airport Summary

- ATL has had numerous infrastructure improvements
- LGA
  - congestion issues due to heavy demand
  - two runway configuration affects operations
- IAD historical data affected by runway renovation

	% of Predictions Correct	
Airport	**Training**	**Test**
PHL	69%	75%
EWR	59%	51%
ORD	71%	70%
ATL	52%	34%
LGA	47%	36%
DCA	75%	58%
IAD	45%	32%
JFK	49%	62%

Air Traffic Management Planning

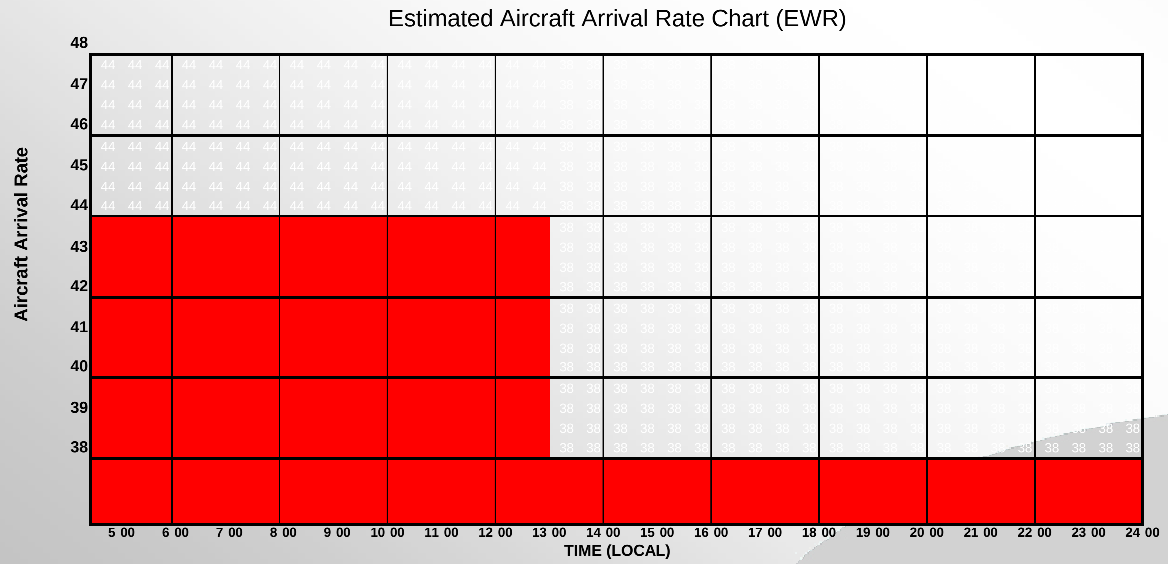
- Schedule congestion can be predicted based on available tools
- Weather prediction tool will predict weather delays caused by reduced capacity
- Tool provides time
  - Managers have more time to formulate response
  - More time to move resources

Summary

- To make the National Airspace System run more efficiently, techniques to more effectively use the limited airport capacity must be developed
- Limited time is available to plan out alternate options that may better alleviate flow problems
- Predictive tools are required to provide advance notice of future air traffic delays.

Conclusions: DST

- SVM predicts three capacity level
  - Normal operations - Green
  - Moderately reduced operations –Amber
  - Severely reduced operations – Red
- Model allows GDP to be derived from AARs for specific time periods



Future Work

- Proper data size set
  - More data points typically improve performance for training data
  - More data points over-fit the data
- New York area airports
  - Runway configuration and congestion at LGA cause delays
  - JFK has an inconsistent AAR because of noise requirements
  - Use Newark to predict JFK and LGA
- Factors other than weather
  - This research focused on weather factors only
  - Additional factors could lead to over-fit
- Data Mining
  - Researchers can analyze controller actions based on a given forecast
  - Are controllers allowing a appropriate amount of risk to support current technology

Questions?

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Backups

Lagrangian Duality

$$L(w,b,\alpha)=\frac{1}{2}w^T w-\sum_{i=1}^{l}\alpha_i\{y_i[w^T x_i+b]-1\} \quad (1)$$

- L must be minimized with respect to *w* and *b* and maximized with respect to nonnegative α
- The objective function and the constraint are convex and KKT conditions are necessary and sufficient conditions for a maximum of the equation

$$\frac{\partial L}{\partial w_0}=0\text{, i.e.,}\qquad w_0=\sum_{i=1}^{l}\alpha_i y_i x_i\text{ ,}\quad (2)$$

$$\frac{\partial L}{\partial b_0}=0\text{, i.e.,}\qquad \sum_{i=1}^{l}\alpha_i y_i=0 \qquad (3)$$

Lagrangian Duality (cont.)

At the solution point the products between dual variables and constraints equals zero

$$\alpha_i \left\{ y_i \left[w^T x_i + b \right] - 1 \right\} = 0, \quad i = 1, l \quad (4)$$

Substituting (2) and (3) into (1)

$$L_d(\alpha) = \sum_{i=1}^{l} \alpha_i - \frac{1}{2} \sum_{i,j=1}^{l} y_i y_j \alpha_i \alpha_j x_i^T x_j$$

In order to find the optimal hyperplane *L* has to be maximized

$$\alpha_i \geq 0, \quad i = 1, l$$

$$\sum_{i=1}^{l} \alpha_i y_i = 0$$

Planning Staff

- TFM Commander – responsible for the NAS
- Chief of Staff – supervises the staff
- Operations Officer – execution of the plan
- Intelligence Officer – maintains awareness of obstacles
- Personnel Officer – personnel status
- Resource Officer – equipment status

Results – Training Data

	Sensitivity	Specificity	PPV	NPV	% Correct
EWR	0.53	0.85	0.71	0.72	0.72
ORD	0.29	0.95	0.69	0.79	0.78
ATL	0.77	0.70	0.74	0.74	0.74
PHL	0.46	0.95	0.77	0.82	0.81
LGA	0.71	0.71	0.75	0.67	0.71
JFK	0.83	0.90	0.93	0.77	0.86
DCA	0.34	0.96	0.70	0.85	0.84
IAD	0.20	0.96	0.71	0.71	0.71
Overall	0.41	0.89	0.78	0.77	0.77

- Sensitivity – Of all GDP airports how many are identified by the SVM
- Specificity – Proportion of non-GDP airports that are identified by the SVM
- Positive predictive value – Probability that if the SVM predicts a GDP that one actually occurs
- Negative predictive value – Probability that if the SVM predicts no GDP that one does not occur

Nonlinear Method

$$\max \sum_{i=1}^{k} \alpha_{\mathrm{i}} - \frac{1}{2}\alpha^T Y\left(\Phi(X)^T \Phi(X)\right)Y\alpha$$

$$s.t. \quad \sum_{i=1}^{k} y_i \alpha_i = 0$$

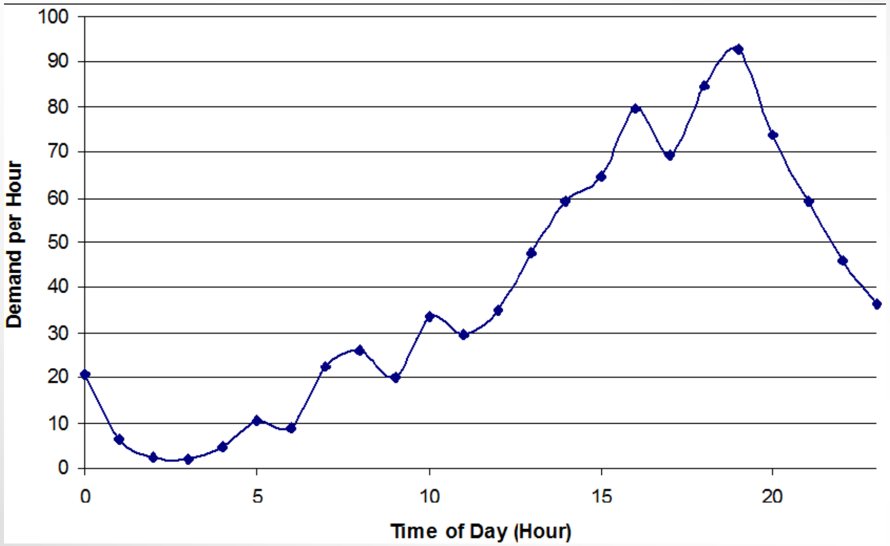
$$0 \le \alpha_i \le C$$

Dual Formulation

$$\mathrm{K}(x, z) = \Phi(x)^T \Phi(z)$$

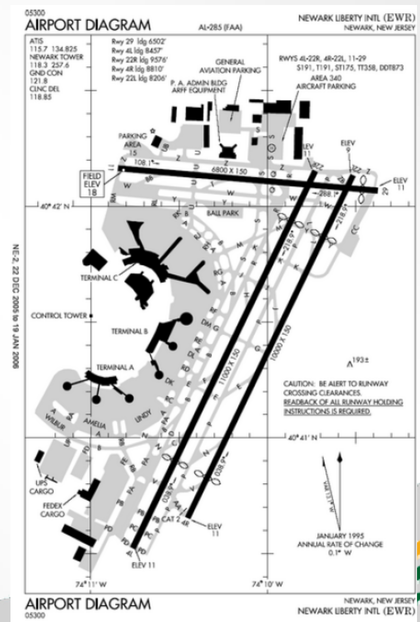
Kernel Function

Newark Results

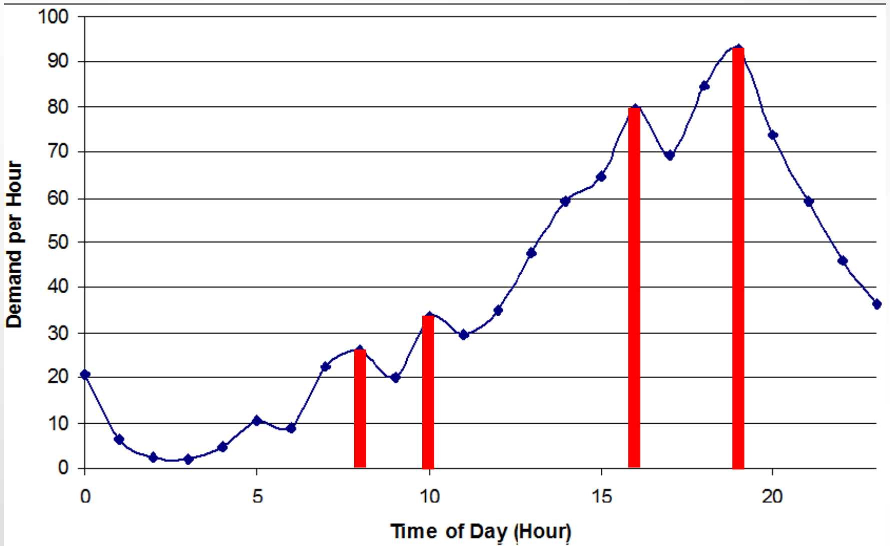


Time	Divider	Sensitivity	Specificity	PPV	NPV	Correct
0800	41	0.37	0.92	0.69	0.75	0.74
	43	0.72	0.71	0.71	0.72	0.71
1000	41	0.35	0.94	0.73	0.76	0.76
	43	0.73	0.72	0.70	0.74	0.72
1600	41	0.39	0.92	0.74	0.73	0.74
	43	0.52	0.83	0.74	0.64	0.67
1900	41	0.41	0.92	0.72	0.74	0.74
	43	0.58	0.77	0.71	0.66	0.68
	Combined	0.53	0.85	0.71	0.72	0.72

Time	Divider	Sensitivity	Specificity	PPV	NPV	Correct
0800	41	0.43	0.95	0.70	0.87	0.85
	43	0.10	0.99	0.91	0.45	0.48
1000	41	0.43	0.98	0.83	0.88	0.87
	43	0.12	0.99	0.92	0.48	0.51
1600	41	0.23	1.00	1.00	0.58	0.62
	43	0.26	1.00	1.00	0.51	0.59
1900	41	0.24	0.98	0.91	0.59	0.63
	43	0.20	1.00	1.00	0.49	0.55
	Combined	0.21	0.98	0.91	0.60	0.64

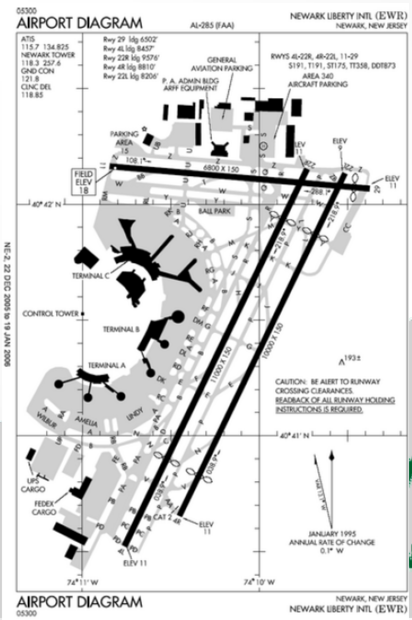


Newark Results



EWR Training Data 2002-2006			
Time	AAR	% of Predictions Correct	% of Actual AAR Occurrence
800	37	69%	17%
	42	30%	34%
	45	74%	48%
1000	37	73%	15%
	42	29%	35%
	45	75%	50%
1600	37	74%	19%
	42	20%	16%
	47	64%	65%
1900	37	72%	20%
	42	24%	21%
	47	67%	59%

EWR Testing Data Jan-Jun 2007			
Time	AAR	% of Predictions Correct	% of Actual AAR Occurrence
800	37	68%	11%
	42	0%	1%
	45	48%	89%
1000	37	83%	10%
	42	0%	1%
	45	49%	90%
1600	37	100%	11%
	42	0%	4%
	47	52%	85%
1900	37	91%	12%
	42	0%	1%
	47	43%	87%



Newark Results (cont.)

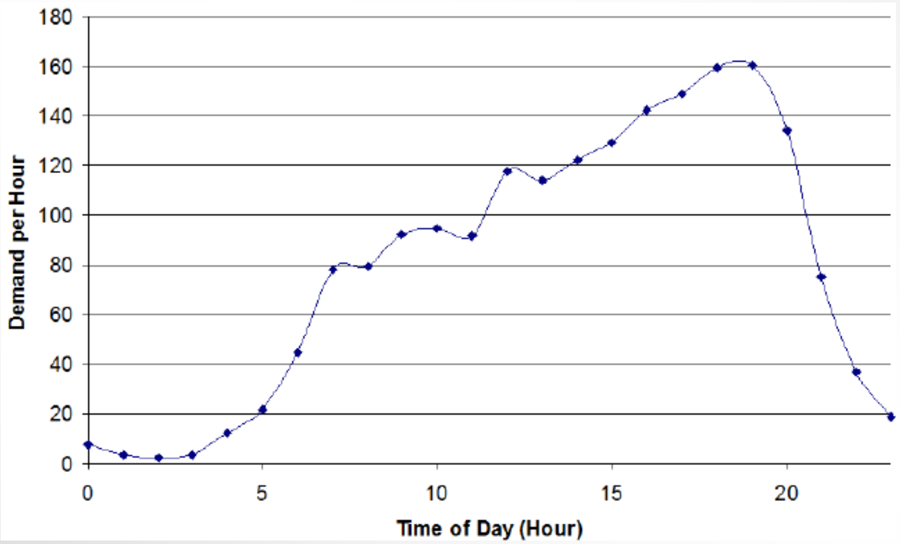
Training

			Predicted AAR		
Time	Actual	Accuracy	37	42	45
0800	37	0.695	221	34	63
	42	0.299	223	188	217
	45	0.735	153	80	647
1000	37	0.727	202	23	53
	42	0.292	230	188	226
	45	0.750	140	86	678
1600	37	0.738	254	28	62
	42	0.198	126	58	109
	47	0.641	267	160	762
1900	37	0.723	263	33	68
	42	0.244	139	93	149
	47	0.665	235	127	719

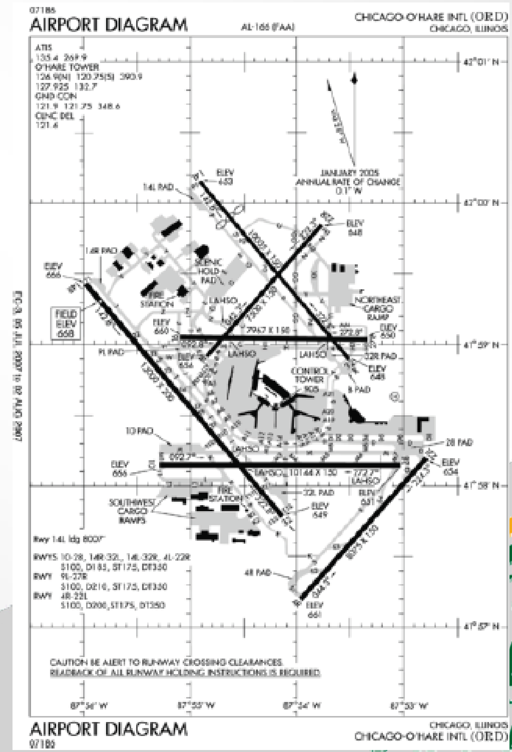
Test

			Predicted AAR		
Time	Actual	Accuracy	37	42	45
0800	37	0.684	13	4	2
	42	0.000	0	0	1
	45	0.481	21	61	76
1000	37	0.833	15	1	2
	42	0.000	1	0	0
	45	0.488	19	64	79
1600	37	1.000	20	0	0
	42	0.000	8	0	0
	47	0.516	60	14	79
1900	37	0.909	20	1	1
	42	0.000	2	0	0
	47	0.433	63	26	68

O’Hare Results



Time	Divider	Sensitivity	Specificity	PPV	NPV	Correct
0800	90	0.33	0.95	0.69	0.82	0.80
	96	0.31	0.93	0.69	0.72	0.72
1000	90	0.28	0.96	0.69	0.82	0.81
	96	0.31	0.94	0.70	0.74	0.74
1200	90	0.30	0.96	0.66	0.84	0.82
	96	0.25	0.95	0.70	0.74	0.74
1900	90	0.24	0.98	0.77	0.84	0.84
	96	0.31	0.93	0.68	0.76	0.75
	Combined	0.29	0.95	0.69	0.79	0.78



Time	Divider	Sensitivity	Specificity	PPV	NPV	Correct
0800	90	0.32	0.96	0.77	0.77	0.77
	96	0.45	0.93	0.75	0.77	0.77
1000	90	0.48	0.96	0.78	0.85	0.84
	96	0.46	0.95	0.81	0.80	0.80
1200	90	0.38	0.94	0.76	0.76	0.76
	96	0.32	0.95	0.79	0.69	0.71
1900	90	0.18	0.99	0.91	0.74	0.75
	96	0.25	0.94	0.72	0.65	0.66
	Combined	0.35	0.95	0.78	0.75	0.76

O'Hare Results (cont.)

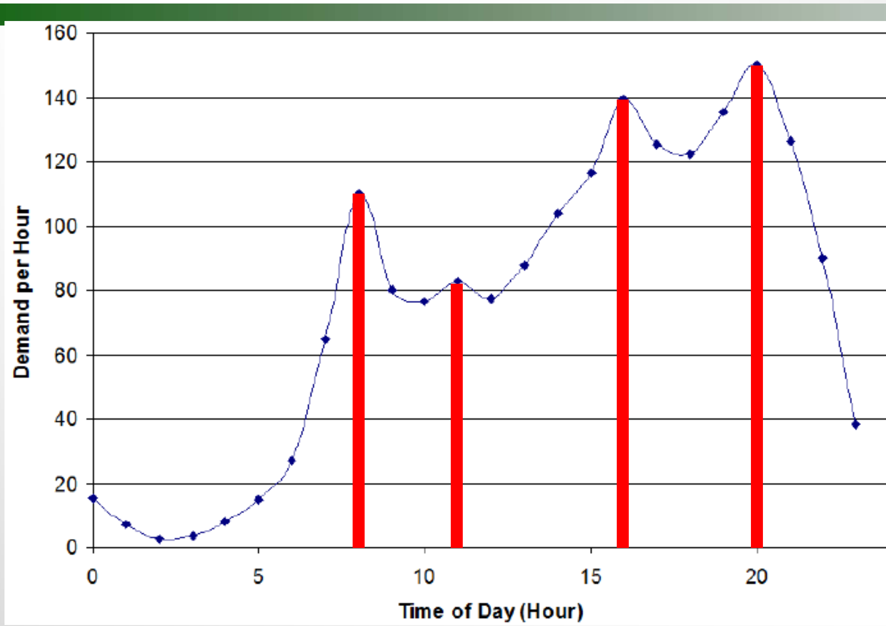
Training

			Predicted AAR		
Time	Actual	Accuracy	80	90	100
0800	80	0.687	147	15	52
	90	0.213	24	17	39
	100	0.725	268	154	1110
1000	80	0.687	112	10	41
	90	0.191	41	18	35
	100	0.744	252	149	1168
1200	80	0.657	115	16	44
	90	0.211	11	8	19
	100	0.745	257	155	1201
1900	80	0.771	84	8	17
	90	0.182	58	28	68
	100	0.759	214	163	1186

Test

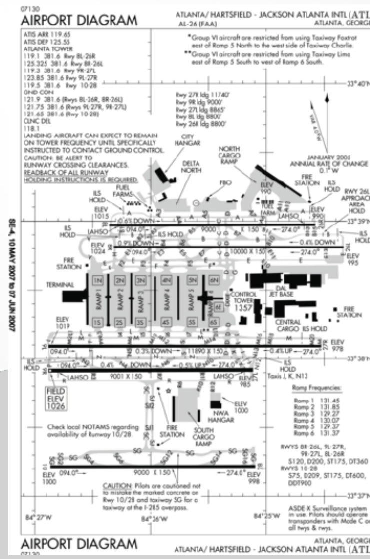
			Predicted AAR		
Time	Actual	Accuracy	80	90	100
0800	80	0.800	17	0	5
	90	0.000	11	0	4
	100	0.724	25	7	112
1000	80	0.778	21	1	5
	90	0.000	4	0	2
	100	0.773	19	11	118
1200	80	0.778	22	1	6
	90	0.000	1	0	0
	100	0.717	35	10	106
1900	80	0.900	10	1	0
	90	0.100	8	1	7
	100	0.640	37	16	101

Atlanta Results



ATL Training Data 2002-2006			
Time	AAR	% of Predictions Correct	% of Actual AAR Occurrence
800	104	74%	33%
	120	36%	35%
	128	65%	31%
1100	104	72%	31%
	120	37%	37%
	128	64%	32%
1600	104	69%	30%
	120	40%	68%
	128	67%	2%
2000	104	68%	11%
	120	42%	87%
	128	59%	2%

ATL Testing Data Jan-Jun 2007			
Time	AAR	% of Predictions Correct	% of Actual AAR Occurrence
800	104	67%	15%
	120	22%	52%
	128	63%	33%
1100	104	76%	16%
	120	17%	45%
	128	46%	40%
1600	104	68%	20%
	120	18%	77%
	128	60%	3%
2000	104	80%	6%
	120	20%	92%
	128	60%	3%



Atlanta Results (cont.)

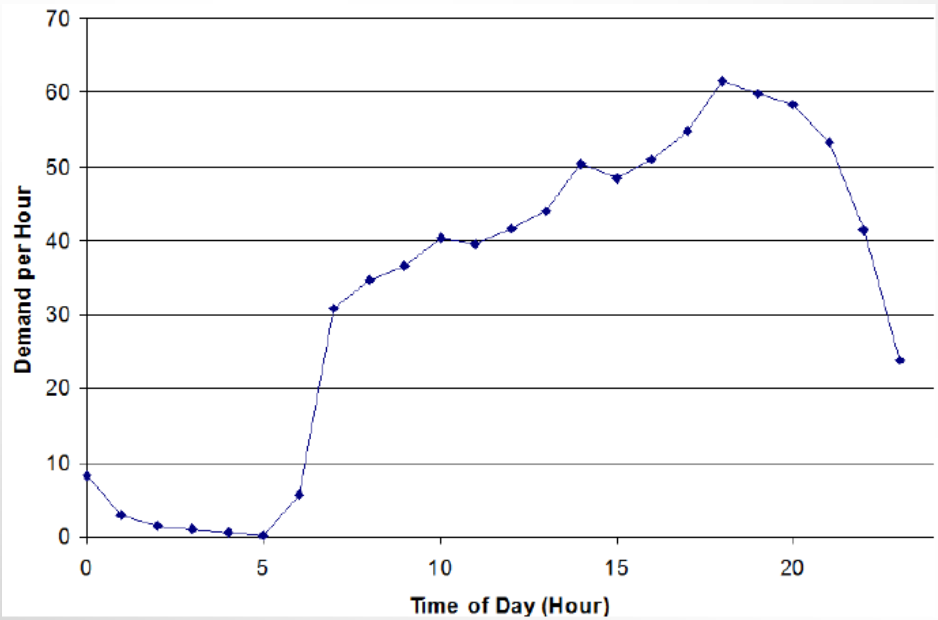
Training

			Predicted AAR		
Time	Actual	Accuracy	104	120	128
0800	104	0.74	453	96	60
	120	0.36	222	229	193
	128	0.65	69	131	373
1100	104	0.72	399	98	60
	120	0.37	234	247	195
	128	0.64	68	144	380
1600	104	0.69	378	126	42
	120	0.40	316	494	425
	128	0.67	5	10	30
2000	104	0.68	132	46	16
	120	0.42	388	675	528
	128	0.59	3	14	24

Test

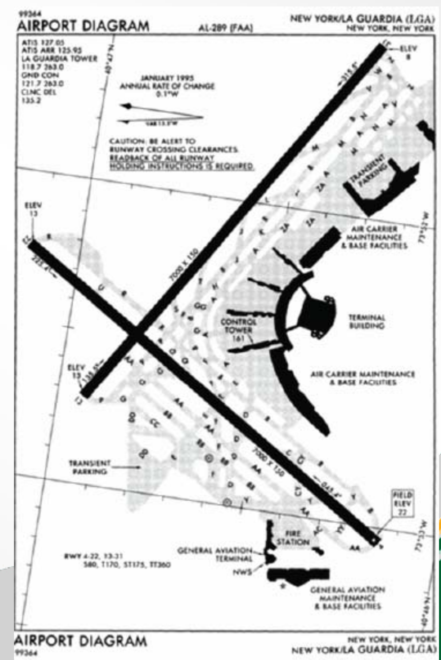
			Predicted AAR		
Time	Actual	Accuracy	104	120	128
0800	104	0.67	18	6	3
	120	0.18	39	21	34
	128	0.63	16	6	38
1100	104	0.76	22	4	3
	120	0.17	38	14	29
	128	0.46	23	16	33
1600	104	0.68	25	6	6
	120	0.18	44	25	70
	128	0.60	1	1	3
2000	104	0.80	8	1	1
	120	0.20	57	34	75
	128	0.60	1	1	3

LaGuardia Results



Time	Divider	Sensitivity	Specificity	PPV	NPV	Correct
0700	36	0.32	0.89	0.66	0.66	0.66
	39	0.91	0.55	0.82	0.73	0.80
1000	36	0.41	0.84	0.64	0.67	0.66
	39	0.90	0.55	0.82	0.70	0.79
1400	36	0.35	0.88	0.67	0.66	0.67
	39	0.93	0.35	0.77	0.68	0.76
1800	36	0.27	0.92	0.67	0.66	0.67
	39	0.98	0.11	0.70	0.73	0.70
	Combined	0.71	0.71	0.75	0.67	0.71

Time	Divider	Sensitivity	Specificity	PPV	NPV	Correct
0700	36	0.05	0.97	0.43	0.69	0.68
	39	0.07	0.97	0.80	0.33	0.35
1000	36	0.11	0.98	0.67	0.72	0.71
	39	0.08	0.94	0.77	0.29	0.33
1400	36	0.17	0.98	0.75	0.74	0.74
	39	0.32	0.83	0.87	0.27	0.44
1800	36	0.19	0.96	0.64	0.77	0.76
	39	0.79	0.43	0.76	0.46	0.68
	Combined	0.26	0.92	0.77	0.55	0.59



LaGuardia Results (cont.)

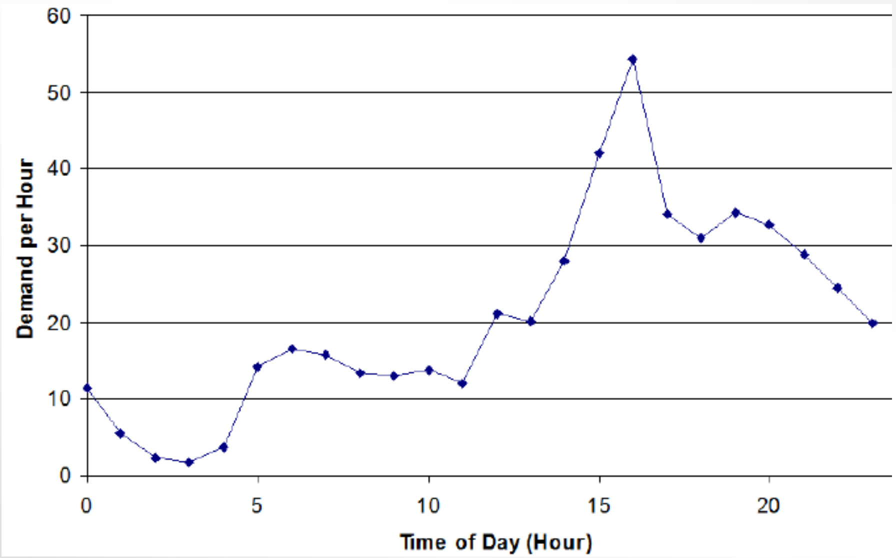
Training

			Predicted AAR		
Time	Actual	Accuracy	32	37	40
0700	32	0.657	238	71	53
	37	0.389	434	405	201
	40	0.729	61	54	309
1000	32	0.637	303	108	65
	37	0.380	379	350	191
	40	0.709	60	65	305
1400	32	0.670	258	90	37
	37	0.341	446	397	320
	40	0.683	37	51	190
1800	32	0.668	189	67	27
	37	0.308	505	448	500
	40	0.733	12	12	66

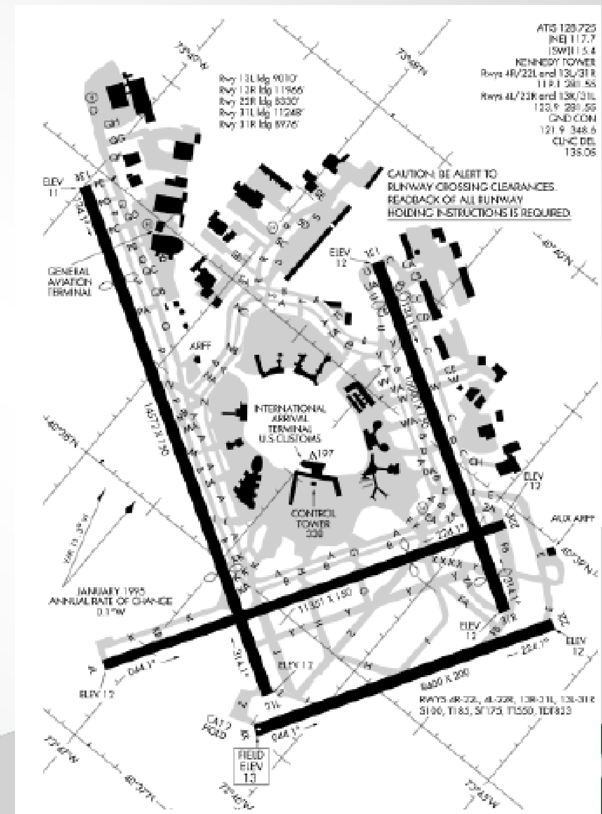
Test

			Predicted AAR		
Time	Actual	Accuracy	32	37	40
0700	32	0.429	3	4	0
	37	0.667	3	2	2
	40	0.333	51	61	56
1000	32	0.667	6	2	1
	37	0.333	2	2	2
	40	0.295	47	70	49
1400	32	0.750	9	3	0
	37	0.325	20	13	7
	40	0.271	24	70	35
1800	32	0.643	9	5	0
	37	0.487	29	57	31
	40	0.460	9	18	23

JFK Results



Time	Divider	Sensitivity	Specificity	PPV	NPV	Correct
1600	49	0.30	0.92	0.74	0.63	0.65
	53	0.93	0.36	0.80	0.65	0.78



Time	Divider	Sensitivity	Specificity	PPV	NPV	Correct
1600	49	0.30	0.95	0.70	0.77	0.76
	53	0.91	0.51	0.83	0.68	0.80

JFK Results (cont.)

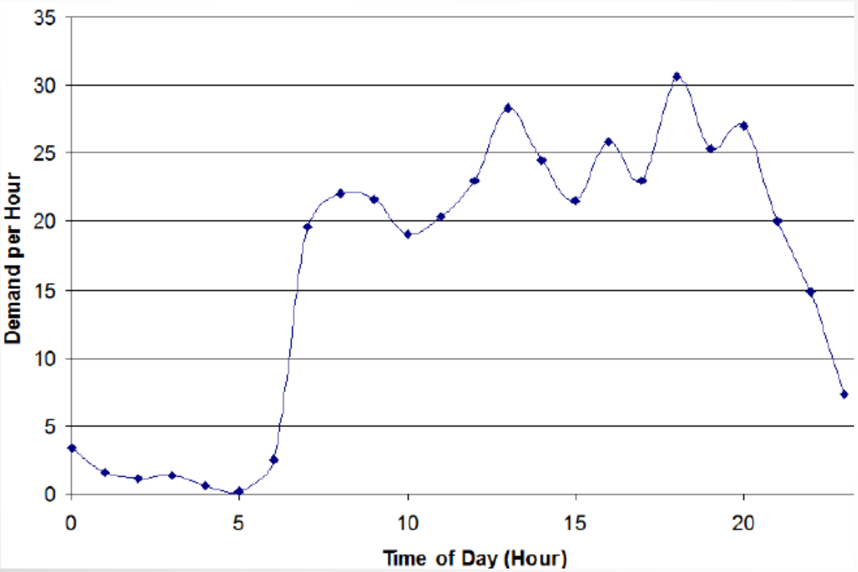
Training

			Predicted AAR		
Time	Actual	Accuracy	35	51	53
1600	35	0.737	233	36	47
	51	0.393	490	493	273
	53	0.658	64	23	167

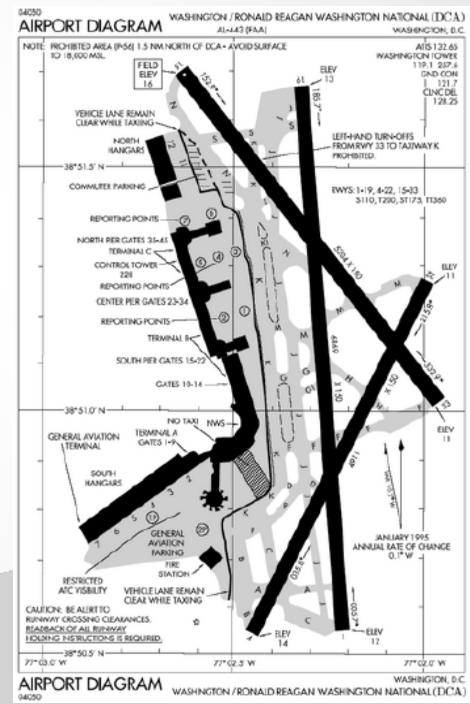
Test

			Predicted AAR		
Time	Actual	Accuracy	35	51	53
1600	35	0.696	16	2	5
	51	0.590	28	72	22
	53	0.667	9	3	24

Reagan Results



Time	Divider	Sensitivity	Specificity	PPV	NPV	Correct
0800	31	0.33	0.97	0.67	0.89	0.88
	35	0.37	0.94	0.71	0.80	0.78
1300	31	0.32	0.97	0.66	0.90	0.88
	35	0.37	0.95	0.71	0.81	0.79
1600	31	0.32	0.98	0.69	0.91	0.89
	35	0.32	0.94	0.67	0.79	0.78
1800	31	0.30	0.98	0.68	0.91	0.89
	35	0.37	0.95	0.73	0.80	0.79
	Combined	0.34	0.96	0.70	0.85	0.84



Time	Divider	Sensitivity	Specificity	PPV	NPV	Correct
0800	31	0.43	0.96	0.50	0.95	0.92
	35	0.16	0.98	0.87	0.60	0.62
1300	31	0.31	0.95	0.33	0.95	0.91
	35	0.17	0.98	0.88	0.59	0.62
1600	31	0.33	0.95	0.31	0.95	0.91
	35	0.16	0.98	0.87	0.60	0.62
1800	31	0.36	0.95	0.31	0.96	0.91
	35	0.12	0.98	0.83	0.58	0.60
	Combined	0.18	0.96	0.63	0.77	0.76

Reagan Results (cont.)

CATSR

Training

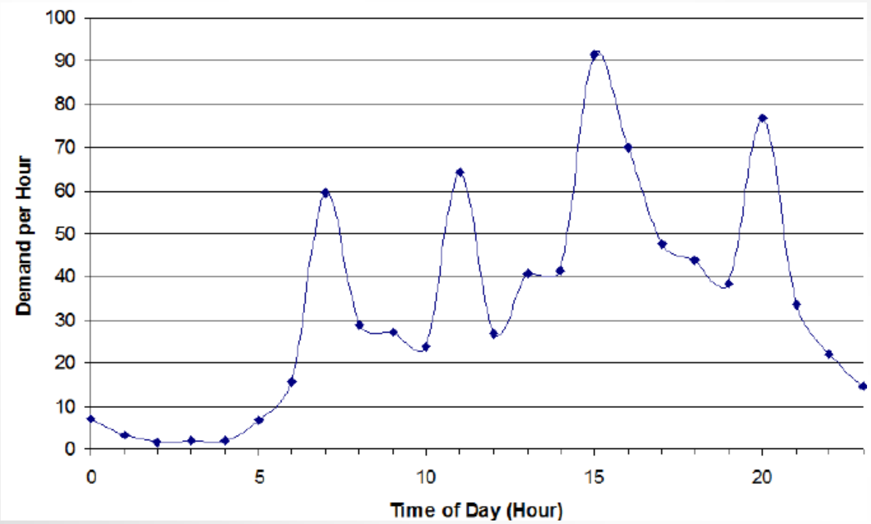
			Predicted AAR		
Time	Actual	Accuracy	27	33	38
0800	27	0.675	83	11	29
	33	0.226	53	28	43
	38	0.796	119	179	1164
1300	27	0.664	77	12	27
	33	0.197	56	24	42
	38	0.807	106	178	1188
1600	27	0.693	70	13	18
	33	0.202	43	25	56
	38	0.795	109	195	1180
1800	27	0.681	64	11	19
	33	0.303	53	44	48
	38	0.801	97	196	1177

Test

			Predicted AAR		
Time	Actual	Accuracy	27	33	38
0800	27	0.500	6	5	1
	33	0.333	1	1	2
	38	0.596	7	60	99
1300	27	0.333	4	6	2
	33	0.750	1	3	0
	38	0.591	8	59	97
1600	27	0.308	4	6	3
	33	0.833	1	5	0
	38	0.605	7	57	98
1800	27	0.308	4	6	3
	33	1.000	0	3	0
	38	0.588	7	61	97

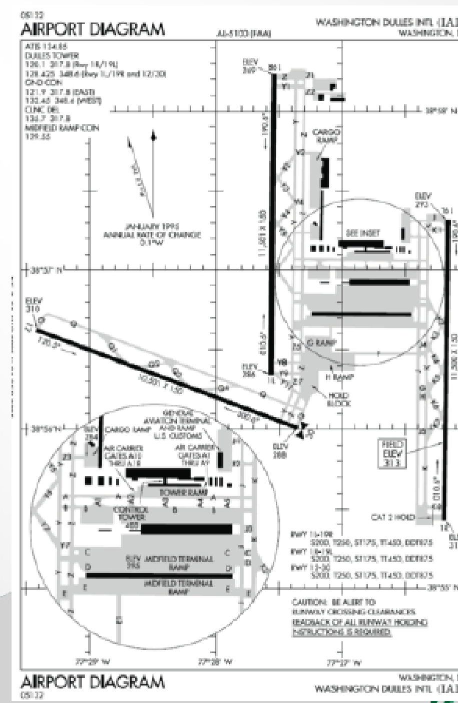
GEORGE MASON UNIVERSITY

Dulles Results



Time	Divider	Sensitivity	Specificity	PPV	NPV	Correct
0700	Under 80	0.33	1.00	1.00	0.71	0.75
	Over 80	0.15	0.96	0.63	0.72	0.72
1100	Under 80	0.23	0.97	0.80	0.72	0.73
	Over 80	0.00	1.00	0.00	0.71	0.71
1500	Under 80	0.27	0.94	0.62	0.77	0.76
	Over 80	0.19	0.93	0.60	0.68	0.67
2000	Under 80	0.23	0.94	0.67	0.71	0.71
	Over 80	0.21	0.93	0.62	0.69	0.68
	Combined	0.20	0.96	0.71	0.71	0.71

Time	Divider	Sensitivity	Specificity	PPV	NPV	Correct
0700	Under 80	0.20	1.00	1.00	0.61	0.65
	Over 80	0.12	0.97	0.60	0.74	0.73
1100	Under 80	0.14	0.95	0.69	0.58	0.59
	Over 80	0.00	1.00	0.00	0.71	0.71
1500	Under 80	0.14	0.98	0.87	0.51	0.54
	Over 80	0.16	0.95	0.63	0.69	0.69
2000	Under 80	0.09	0.96	0.75	0.46	0.48
	Over 80	0.36	0.89	0.56	0.79	0.75
	Combined	0.15	0.96	0.71	0.63	0.64



Dulles Results (cont.)

Training

			Predicted AAR		
Time	Actual	Accuracy	68	80	90
0700	68	0.706	226	61	33
	80	0.428	352	590	438
	90	0.635	15	31	80
1100	68	0.802	138	21	13
	80	0.404	461	669	524
	90	0.000	0	0	0
1500	68	0.623	132	52	28
	80	0.408	346	578	492
	90	0.606	18	60	120
2000	68	0.665	139	45	25
	80	0.355	421	495	480
	90	0.620	44	40	137

Test

			Predicted AAR		
Time	Actual	Accuracy	68	80	90
0700	68	0.842	16	1	2
	80	0.336	58	51	43
	90	0.176	3	1	6
1100	68	0.688	11	3	2
	80	0.273	69	45	51
	90	0.000	0	0	0
1500	68	0.867	13	1	1
	80	0.160	76	24	50
	90	0.625	5	1	10
2000	68	0.750	9	2	1
	80	0.190	80	26	31
	90	0.563	11	3	18

SVM Accuracy

	Sensitivity	Specificity	PPV	NPV	% Correct
EWR	0.53	0.85	0.71	0.72	0.72
ORD	0.29	0.95	0.69	0.79	0.78
ATL	0.77	0.70	0.74	0.74	0.74
PHL	0.46	0.95	0.77	0.82	0.81
LGA	0.71	0.71	0.75	0.67	0.71
JFK	0.83	0.90	0.93	0.77	0.86
DCA	0.34	0.96	0.70	0.85	0.84
IAD	0.20	0.96	0.71	0.71	0.71
Overall	0.41	0.89	0.78	0.77	0.77

- Sensitivity – Of all GDP airports how many are identified by the SVM
- Specificity – Proportion of non-GDP airports that are identified by the SVM
- Positive predictive value – Probability that if the SVM predicts a GDP that one actually occurs
- Negative predictive value – Probability that if the SVM predicts no GDP that one does not occur