Taxi Time Prediction at Schiphol Airport

Final Presentation of the Master Thesis By
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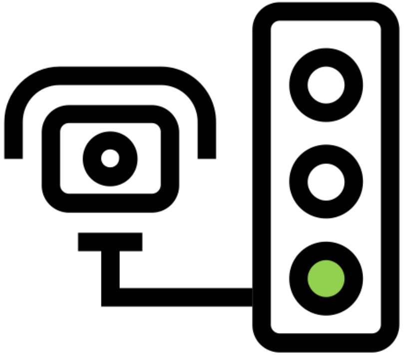
Delft University of Technology
Knowledge Development Centre Mainport Schiphol

June 28, 2021

Practical

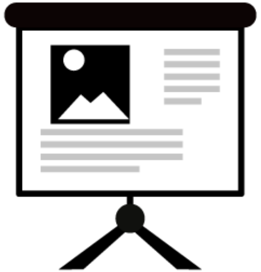


Audience Participation

Go to www.menti.com and use code 4250 4123

Goal

- Let you know what I have done
- Answer your questions



30 minutes

Content

- Research Goal
- Literature Study
- Data Understanding
- Data Preparation
- Predicting
- Results
- Conclusion

Research Goal

Content

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- Literature Study
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- **Research Goal**
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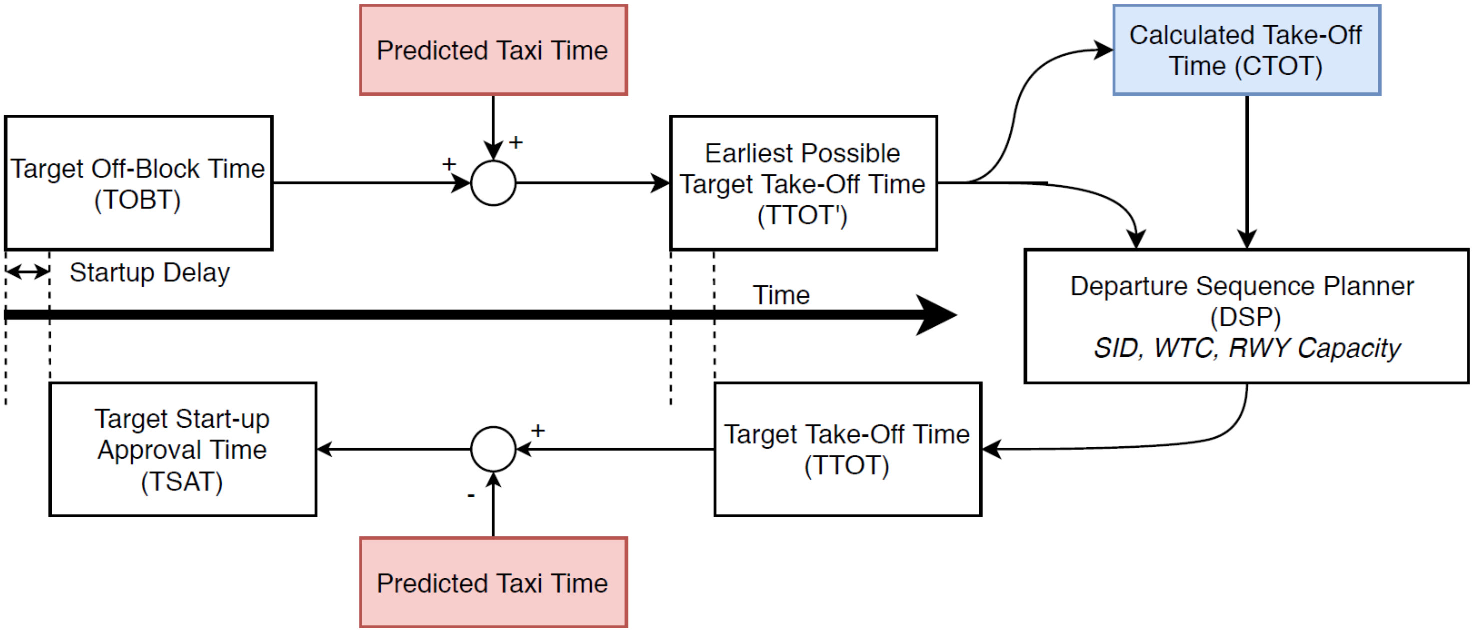
Research Goal



Research Goal

Content

- **Research Goal**
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The objective of this research is to improve taxi-time predictions by analyzing the operational performance of different predictors and input parameters at different prediction horizons.

Research Goal

Content

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The objective of this research is to improve taxi-time predictions by analyzing the operational performance of different predictors and input parameters at different prediction horizons.

Research Goal

Content

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- Eurocontrol [4]

Timelines	Time periode covered	Input	Required Accuracy
Long Term	Off-Block Time - 3h to Off-Block Time - 2h	Predicted static data (current runway in use, and planned stand). If this information is not available then a default value should be used	+/- 7 minutes
Medium Term	Off-Block Time - 2h to Off-Block Time - 30 min	Update static data (current runway in use, and planned stand)	+/- 5 minutes
Short Term	Off-Block Time - 30 min to Actual Off-Block Time	Current runway in use and actual stand	+/- 2 minutes

- European Union [5]

Advanced Surface Movement Guidance and Control Systems (A-SMGCS) shall provide optimised taxi-time and improve predictability of take-off times by monitoring of real surface traffic and by considering updated taxi times in departure management

Content

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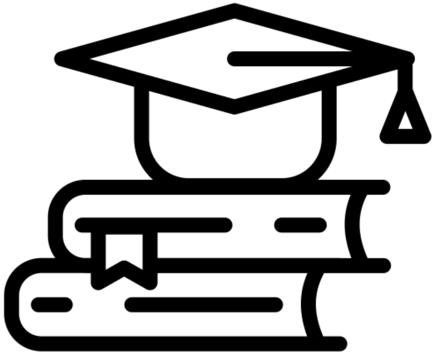
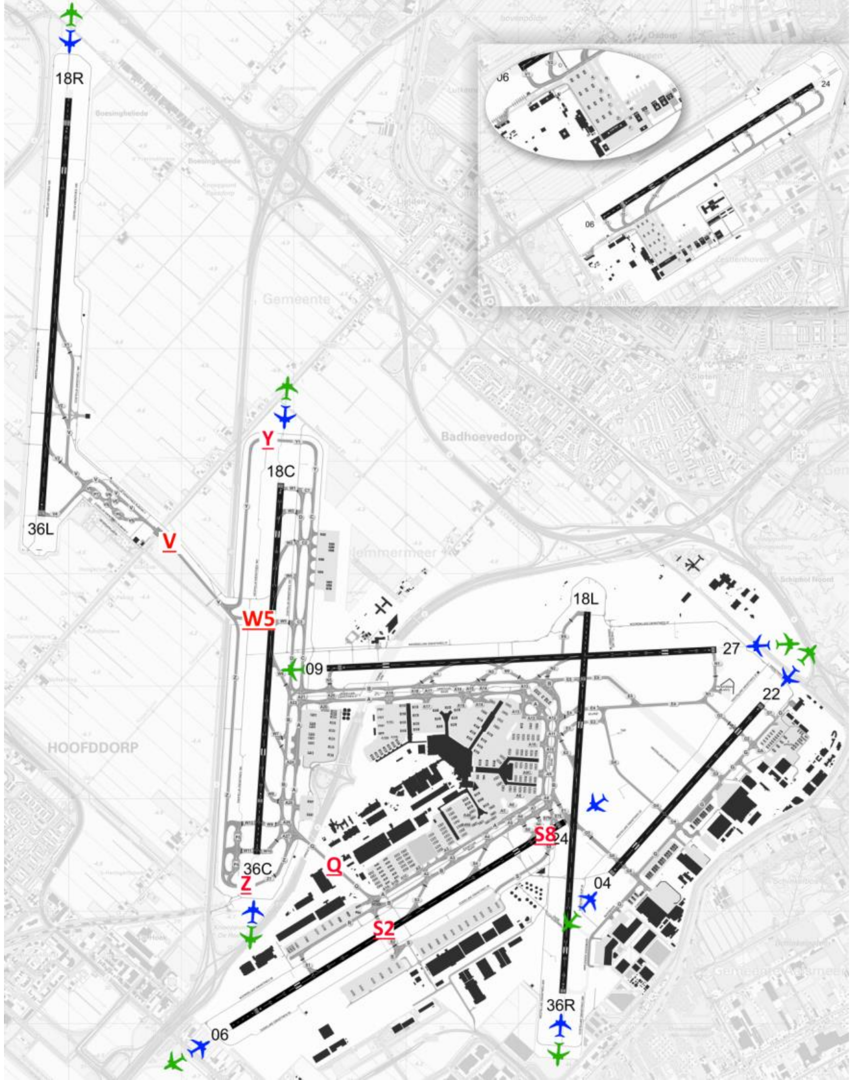
Literature Study

- The foundation of this research
  - Research Goal
    - Operational Performance
    - Prediction Horizon
  - Methodology
    - Model Type Selection
    - Data Selection Technique
    - Performance Feedback





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Data Understanding

Content
- Research Goal
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- **Data Understanding**
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- What does aircraft taxi time depend on?

- Go to www.menti.com and use code 4250 4123

Data Understanding

Content

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- Astra
  vehicle positioning data on the airport surface
- Tower
  flight information available to tower controllers
- Capacity Forecast Schiphol
  expected runway configuration
- Weather
  KNMI weather forecast
- Other
  Airport Maintenance, Airport Geometry, ICAO Doc 8643 Aircraft Type Designators

Luchtverkeersleiding Nederland
Air Traffic Control The Netherlands

Capacity Forecast Schiphol

APP Supervisor : **Schenk, M.M.M.**

Date & Time (LT) : **07-06-2019 14:00**

FRIDAY 07 JUNE 11 UTC TILL SATURDAY 08 JUNE 18 UTC	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**21**	**00**	**03**	**06**	**09**	**12**	**15**	**18**
Visibility 5 km and/or ceiling ≤ 2000 ft (%)	0	0	0	5	20	20	10	0	5	15	30	30	30	20	10
Visibility < 5 km and/or ceiling < 1000 ft (%)	0	0	0	5	15	15	5	0	0	5	10	10	10	5	0
RVR ≤ 1500 m and/or ceiling ≤ 300 ft (%)	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
RVR < 550 m and/or ceiling < 200 ft (%)	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
RVR < 350 m (%)	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Visibility and ceiling	G	G	G	G	G	G	G	G	G	G	G	G	G	G	G
Wind direction (deg)	110	110	120	130	140	200	190	160	170	190	200	200	220	230	230
Windspeed (kt)	18	18	18	17	16	14	13	15	17	23	24	25	27	26	23
Gusts (kt)	26	27	26	25	23	20	19	21	25	35	36	37	40	39	35
Standard deviation wind direction (deg)	25	25	30	30	30	30	30	30	10	10	10	10	15	10	10
Standard deviation wind speed (kt)	3	4	4	5	5	5	5	3	4	4	3	3	4	4	4
Temperature (°C)	20	21	22	22	20	15	15	14	14	13	13	13	14	16	15
Dewpoint (°C)	10	11	12	13	14	12	11	9	10	10	10	10	10	10	9
Snow (%)	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Moderate or heavy snow (%)	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Freezing rain (%)	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
CB (%)	0	0	5	30	50	80	60	0	5	10	15	15	15	15	5
Thunderstorm (%)	0	0	5	20	40	60	30	0	0	0	0	0	0	0	0

	Shortterm	**Longterm**
Visibility and ceiling		
Wind	Btn 15 and 18 UTC near showers gusts 35-40 kt, risk around 45 kt.	
Temperature/dewpoint		
Precipitation	Btn 15 and 18 UTC tempo SHRA/TSRA, risk +TSRA.	Saturday tempo RA/SHRA.
CB in FIR	Fm SW fm 13/14 UTC line of ocnl/frq CB, tops FL300/330, mov NNE 40 kt.	Friday evening in N and NE ocnl/frq CB, tops FL300/330, mov NNE 40 kt, leaving the FIR around 21 UTC. Saturday isol (embd) TCU/CB, tops FL100-150, risk FL200.

ILS degradation:	Runways not available (incl. reason):

Time (UTC)	Planned				Alternative				Taxi Time	Remarks
	Landing		Take Off		Landing		Take Off			
1140-1300	**18R**	-	**09**	**18C**	-	-	-	-		
Capacity	38	-	35	30	-	-	-	-		
1300-1410	**18R**	**18C**	**09**	-	**06**	**18R**	**09**	-		
Capacity	34	34	40	-	34	34	37	-		
1410-1540	**18R**	-	**09**	**18C**	**18R**	-	**18L**	**18C**		
Capacity	38	-	35	30	38	-	37	37		
1540-1820	**18R**	**22**	**18C**	-	-	-	-	-		
Capacity	30	15	37	-	-	-	-	-		
1820-2010	**18R**	-	**09**	**18C**	**18R**	-	**24**	**18L**		
Capacity	38	-	35	30	38	-	37	37		

Meteorological advisor (MAS) will be present:	Date & Time(LT):
Yes	08-06-2019 14:00

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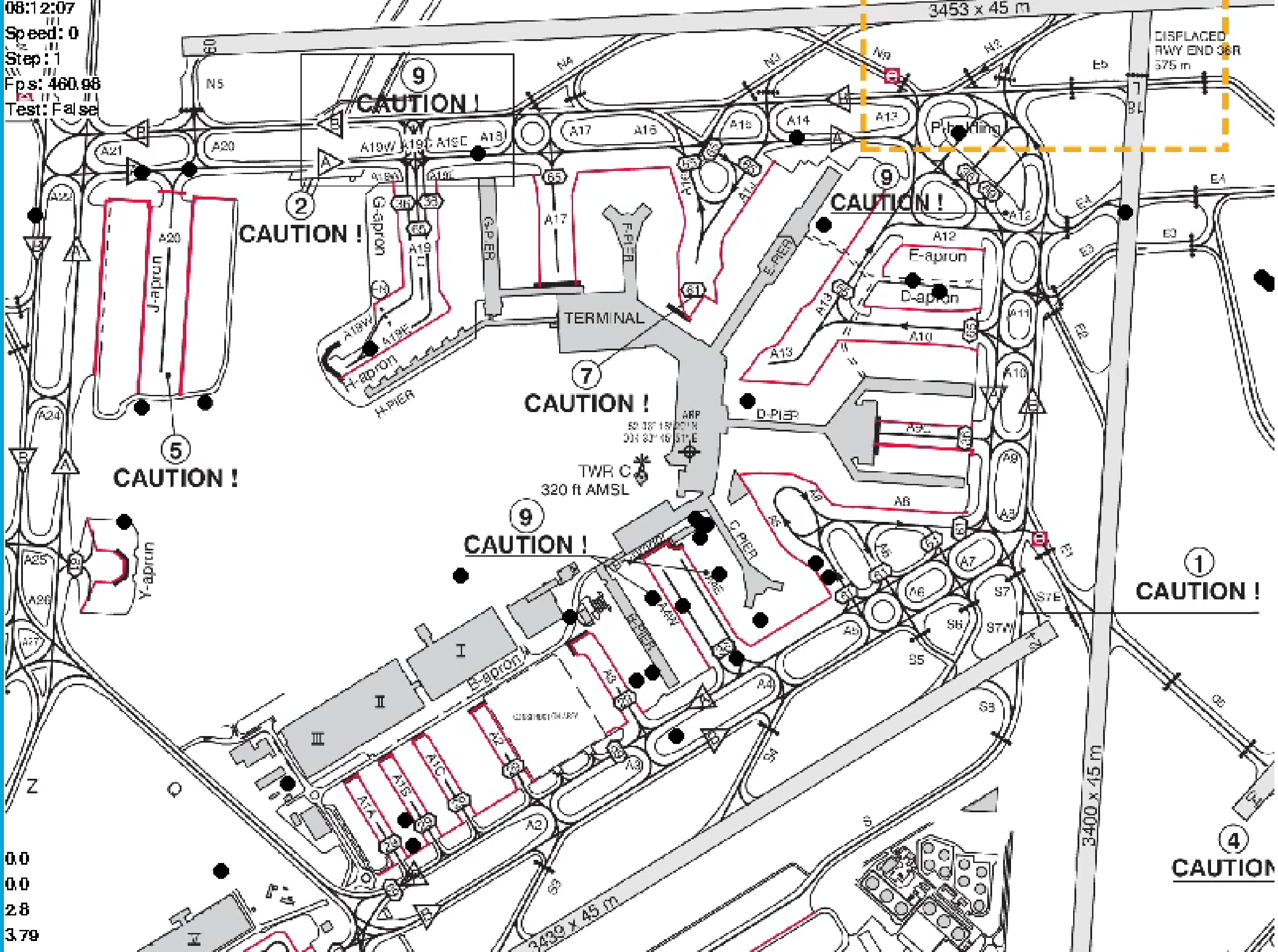


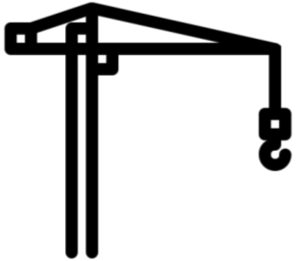
Content

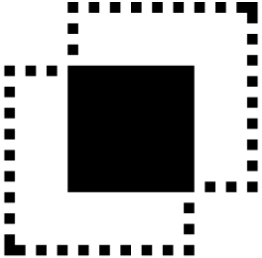

```python
import pygame
# ...
pygame.init()
# ...
ast_data = pd.read_csv(ast_path, delimiter=";", names=ast_names, dtype=ast_dtype")
# ...
time_o = time.time()
while running:
    # Checking Events
    for event in pygame.event.get():
        if event.type == pygame.QUIT: 
            running = False
    # ...
    if speed_on:
        t_step = int( (time.time() - time_o) * speed)
        t += t_step
        if t_step:
            time_o = time.time()
    # ...
    if t_step: # Only when tracking ac (currently always)
        ast_data_t = ast_data.loc[ast_data['t']==t,:].copy()
        ast_data_t['x_screen'] = ((ast_data_t[['x']]-x)*ppm+screen_width/2)
        ast_data_t['y_screen'] = ((ast_data_t[['y']]-y)*-ppm+screen_heihgt/2)
    # ...
    # Drawing
    screen.fill(settings["colors"]["white"])
    if bmap_on:
        screen.blit(bmap, (0,0))
    for x_ac, y_ac in ast_data_t.values[:, -2:]:
        rect_u.append(pygame.draw.circle(screen, black, (x_ac, y_ac), 5))
    pygame.display.flip()
```

Data Preparation


Select


Clean


Construct


Integrate


Format

Content

Data Preparation

Content

Astra

t	f_id	x	y
0	KLM1058	0	0
0	BRW112	100	100
0	UAE9743	-100	-100
...	...	...	...
1	KLM1058	0	100
1	BRW112	100	100
Null	UAE9743	-100	-100
...	...	...	...

Astra Reduced

t	f_id	From	To
0	KLM1058	Null	Gate
50	KLM1058	Gate	Ramp
200	KLM1058	Ramp	Taxiway
1000	KLM1058	Taxiway	Queue
1200	KLM1058	Queue	Runway
...	...	...	...
0	UAE9743	Null	Gate
...	...	...	...

Astra Processed

astra_id	t_taxi	type	18C/36C
KLM0565_1563362061	988	dep	18C/36C
KLM0643_1551975365	587	dep	09/27
KLM0903_1560851730	897	dep	18C/36C
KLM1_1542464104	863	dep	18R/36L
KLM1_1542468346	91	arr	06/24
KLM1_1573914147	441	dep	18L/36R
KLM1_1573917049	789	arr	18R/36L
...	...	...	...

- Departure Taxi Time Construction:

t_taxi = time latest runway entry – time of latest gate area exit

Content


```sql
WITH
astra_t_prior AS (
    SELECT
        t,
        f_id,
        EXTRACT(epoch FROM (t - lag(t) OVER (PARTITION BY f_id ORDER BY t))) AS t_prior
    FROM astra
),
astra_sep_table AS (
    SELECT
        f_id,
        t AS t_start,
        lead(t) OVER (PARTITION BY f_id ORDER BY t) AS t_end,
        concat(f_id, '_', EXTRACT(epoch FROM t)) AS f_id_sep
    FROM astra_t_prior
    WHERE t_prior >= {trk_split_interval} or t_prior IS NULL
),
astra_sep AS (
    SELECT a.astra_id, a.t, a.x, a.y, a.gs, a.f_id, sep.f_id_sep
    FROM astra_sel AS a
    LEFT JOIN
    astra_sep_table AS sep
    ON (a.f_id=sep.f_id) AND (a.t>= sep.t_start) AND ((a.t<sep.t_end) OR sep.t_end IS NULL)
) SELECT * FROM astra_sep
```

Data Preparation

Content

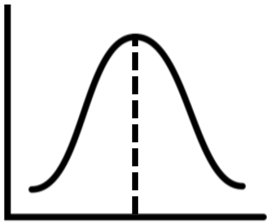
Departures

dep_id	t_taxi	actype	temp
1428_VLG83PW_1554731699	988	A321	20
1428_VLG83VF_1555619743	866	A320	16
1428_WOW4SL_1535474724	784	A321	20
1429_AAL221_1534582378	1169	B772	18
1429_AEA59XR_1545417133	530	B738	10
1429_AFR1337_1534949087	358	E145	23
1429_AFR1741_1574258518	609	A319	6
...	...	...	...

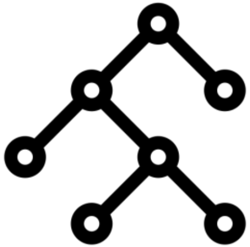
- “Integration Hell”
- Four Prediction Horizons
- Database: 490 GB
  - Astra: ~3,000,000 records / day or ~165 MB / day
  - 2 years worth of data

Content

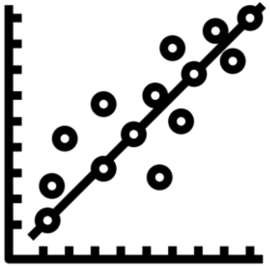
Predicting



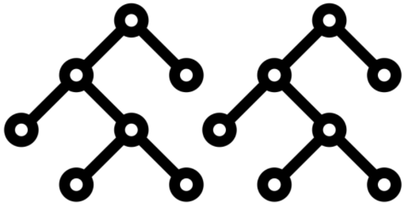
Average



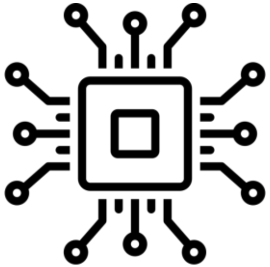
Manual Tree



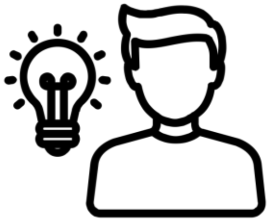
Linear Predictor



Tree-Based Ensemble

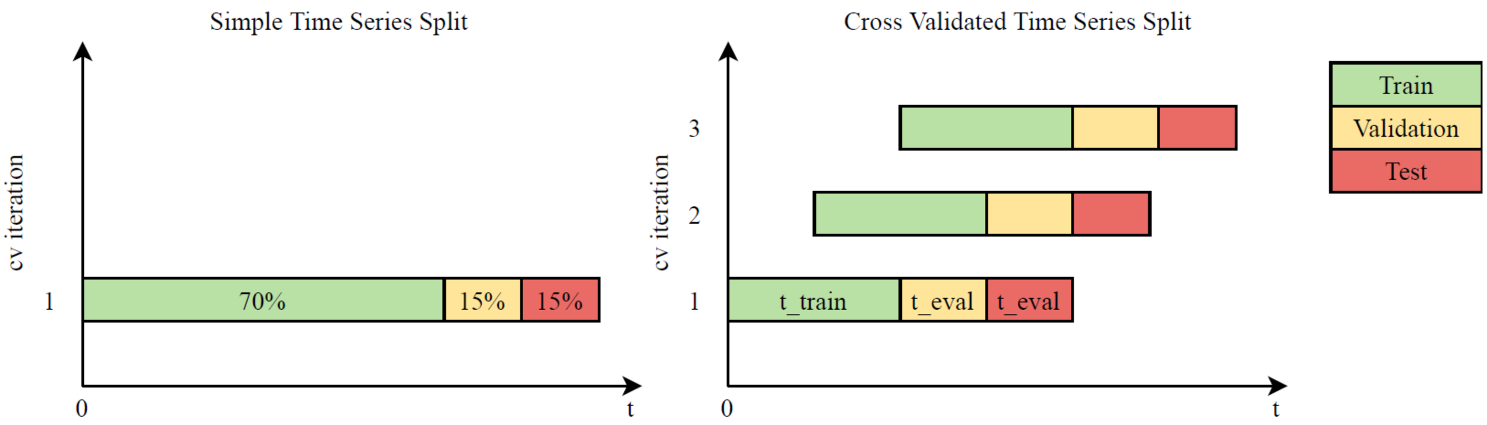


AutoML



Performance Feedback

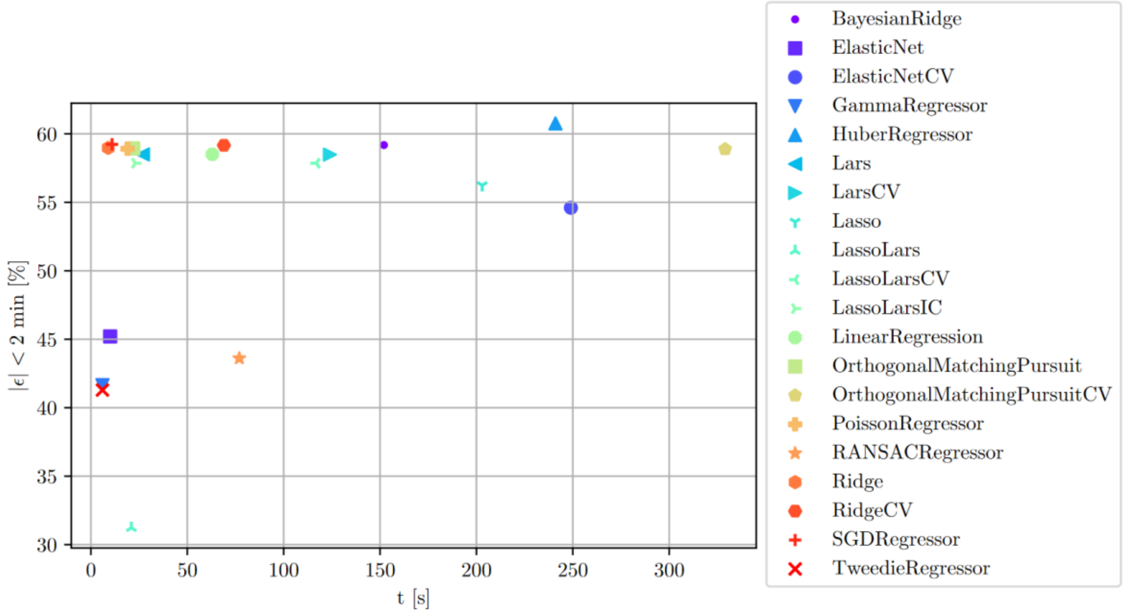
Predicting – Evaluation Technique



- How do we compare performance?
  - A couple seconds don't matter
  - Large errors (outliers) don't matter
- Air traffic controller: $|\epsilon| < 2\,min$ [%]
- Mean Absolute Error over Root Mean Square Error

Predicting – Linear Predictor

Content



- Compare Predictor Variations, Feature Selections, and Parameter

Predicting – Feature Selection

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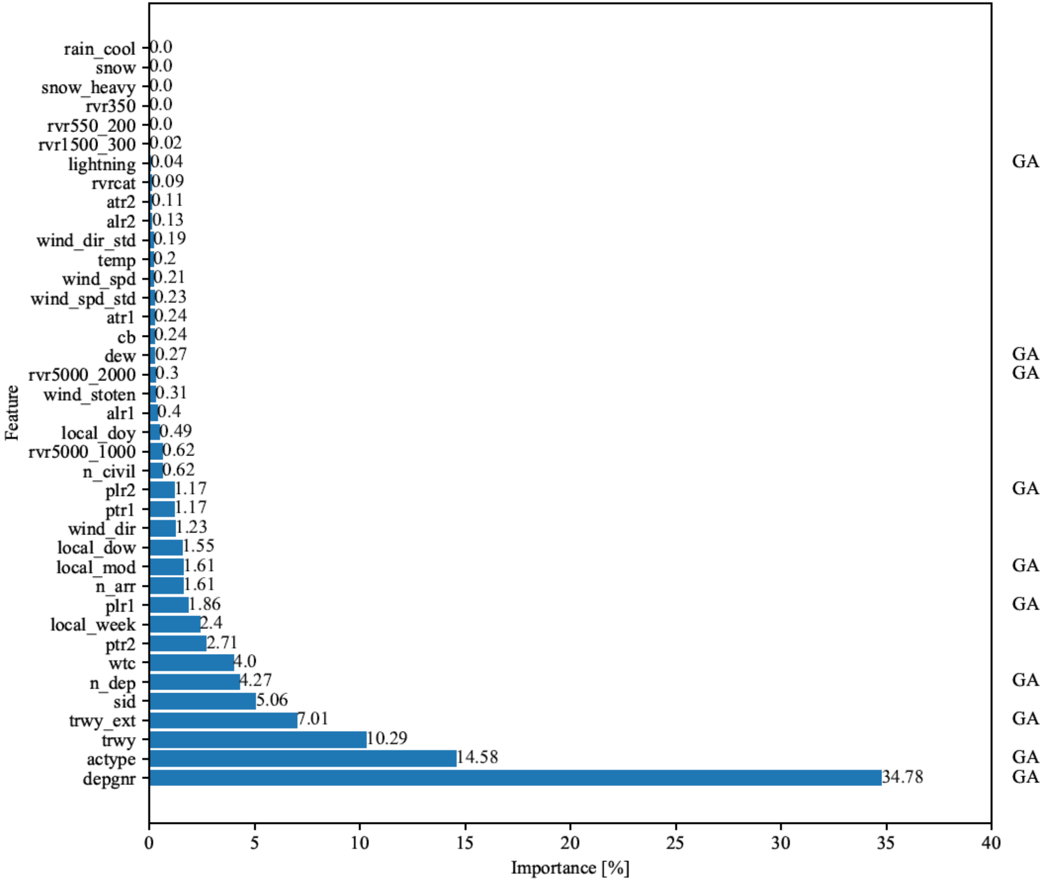

Predicting – AutoML

Content

Forbes

Apr 7, 2020, 10:10am EDT | 2,992 views

AutoML 2.0: Is The Data Scientist Obsolete?

THE VERGE TECH REVIEWS SCIENCE ENTERTAINMENT MORE

GOOGLE TECH ARTIFICIAL INTELLIGENCE

Google's new cloud service lets you train your own AI tools, no coding knowledge required

By James Vincent | Jan 17, 2018, 11:53am EST

TPOT

AutoKeras

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Predicting – Perfromance Feedback

Content
- Research Goal
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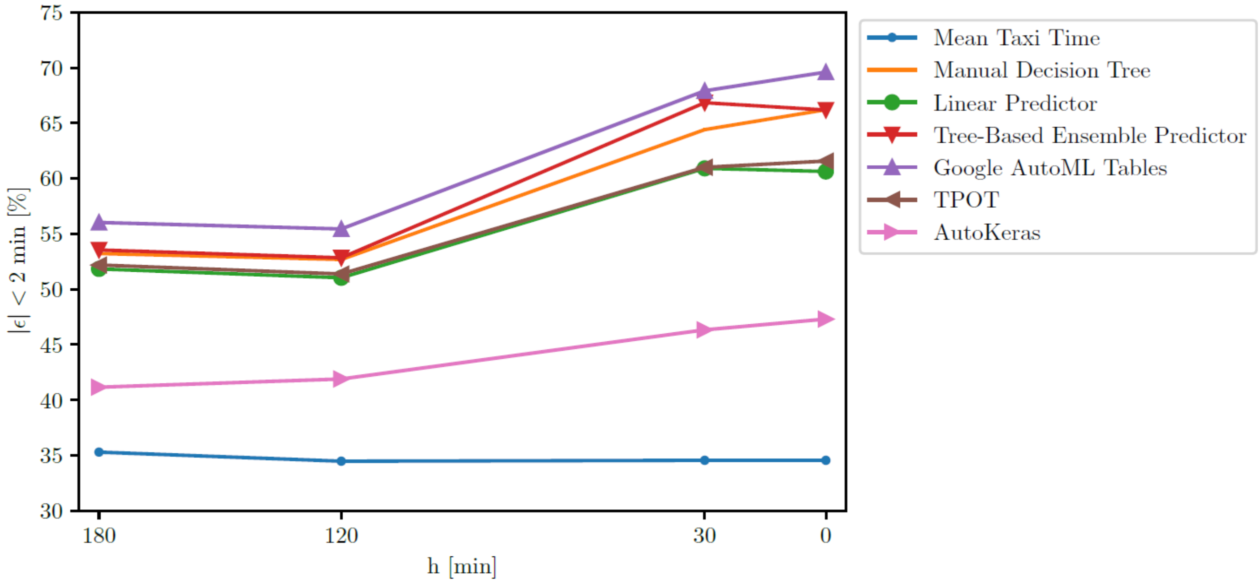
"During certain periods, the taxi time is continuously too short."

- Add a fraction of the recent original predictor error to the original prediction
  - Determine optimal fraction/period
  - Optimal found for 1 hour & 7 days

Performance Feedback	$\|\epsilon\| < 2$ min [%]	MAE [s]	RMSE [s]	$\|\epsilon\| < 5$ min [%]	$\|\epsilon\| < 7$ min [%]
None	61.57	124.39	183.62	92.66	97.17
1 hour & 7 days	61.69	124.86	184.78	92.42	97.05

Results

Content



Performance Feedback	$\lvert\epsilon\rvert < 2$ min [%]	MAE [s]	RMSE [s]	$\lvert\epsilon\rvert < 5$ min [%]	$\lvert\epsilon\rvert < 7$ min [%]
None	60.91	123.55	172.43	92.78	97.45
1 hour & 7 days	60.93	123.99	173.56	92.60	97.34

Results

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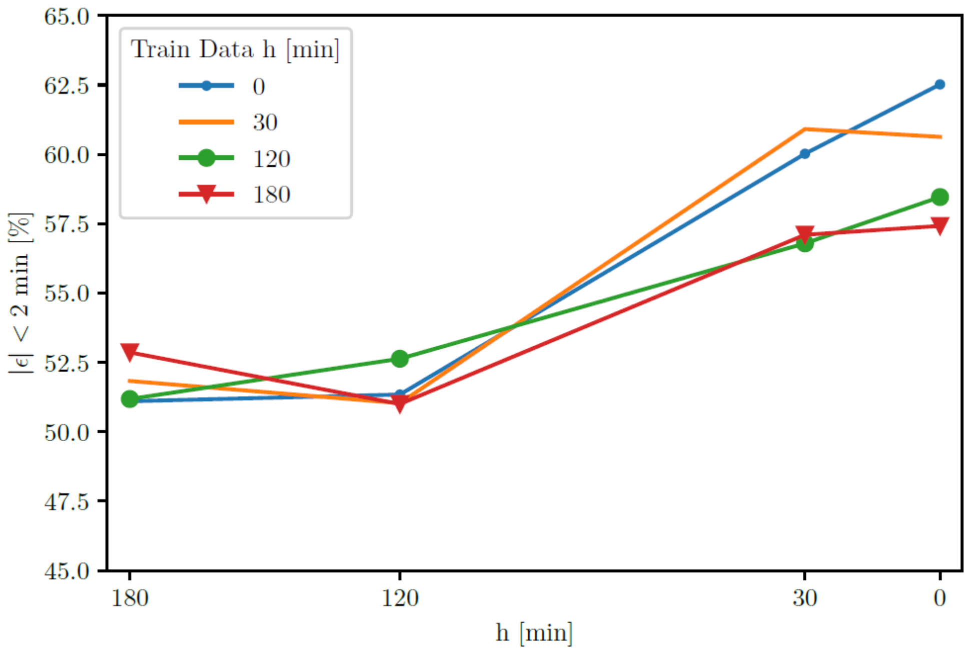
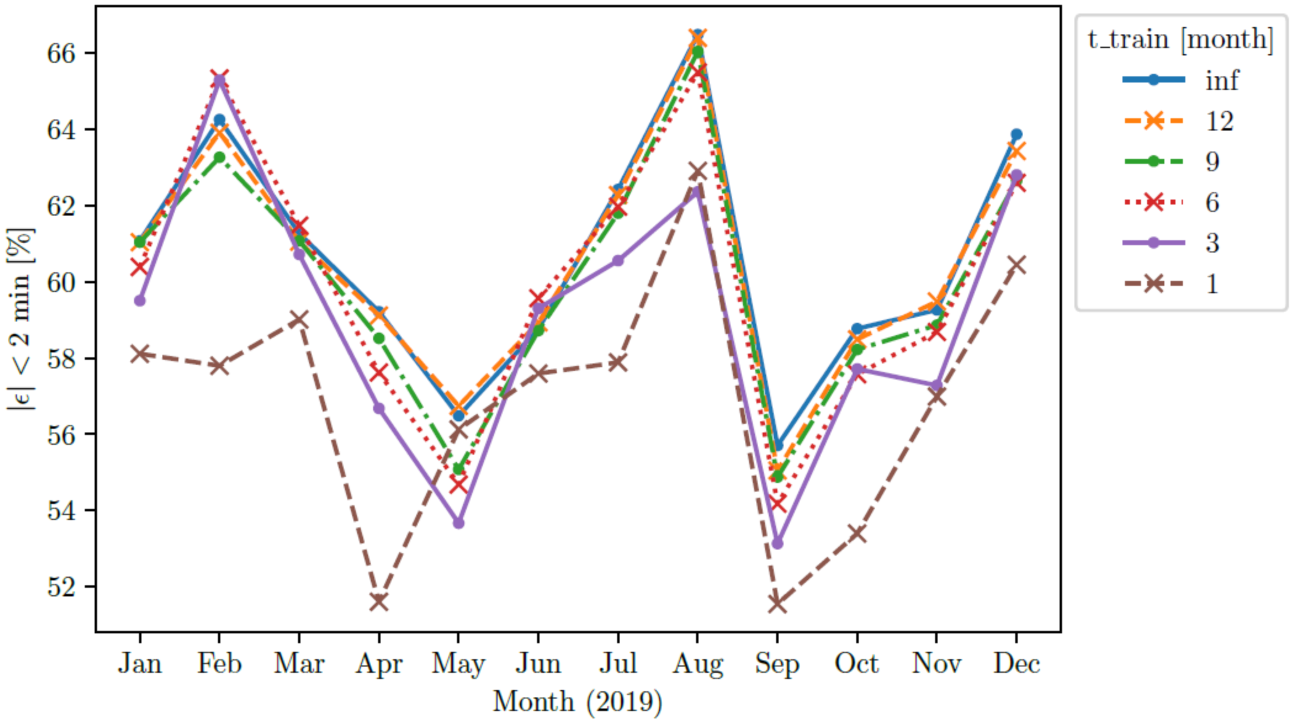


- When to use which model?

Results

Content



Conclusion

- Google AutoML best predictor,
  Tree-Based Ensemble Method close second
- 3.5% $|\epsilon| < 2\ min$ performance gain
- Open source AutoML tools performs worse, likely due to limited computational resources
- Performance feedback does not appear to work

Recommendations

- Determine the impact of taxi time prediction errors
- Analyze the departure process as a whole
- Trade-off complexity versus performance of predictors

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Conclusion

Content

Questions

- Article and more information available at:
  https://github.com/EKPyqh40/Taxi-Time-Prediction-Schiphol-Airport

References

Slide	Reference
2	Microphone made by Freepik from flaticon
	Red light camera by Linh Nguyen from the Noun Project
	Cats by Tenderly, William de Vassconcellos via Unsplash, Ramiz Dedaković via Unsplash
3	Presentation by MCruz from wikimedia
	Discussion by I Create Stuff from the Noun Project
	Changi Airport traffic jam by Simon_sees from Australia
	Pollution by Aficons from the Noun Project
	Air traffic control tower by Creative Stall from the Noun Project
	Coffee break by Nicolas Vicent from the Noun Project
	Demolition by Adrien Coquet from the Noun Project
	Ambulance Chaser by Simon Child from the Noun Project
	Shrug by Andrew Doane from the Noun Project
	Eurocontrol. (2017). Airport Collaborative Decision-Making (A-Cdm) Implementation Manual . Airport Collaborative Decision-Making (A-CDM) Implementation Manual (5.0 ed.).

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[4] Eurocontrol. (2017). Airport Collaborative Decision-Making (A-Cdm) Implementation Manual . Airport Collaborative Decision-Making (A-CDM) Implementation Manual (5.0 ed.).

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References

[6] European Commission. (2014). Commission Implementing Regulation (EU) No 716/2014 of 27 June 2014 on the establishment of the Pilot Common Project supporting the implementation of the European Air Traffic Management Master Plan Text with EEA relevance . Official Journal of the European Union, 19–44.

[7] P. Chapman, J. Clinton, R. Kerber, T. Khabaza, T. Reinartz, C. Shearer, and R. Wirth. CRISP-DM 1.0 Step-by-step data mining guide, 2000.

[8] Residuals for Linear Regression Fit by Thomas.haslwanter from wikimedia

Random Forest by sachin modgekar from the Noun Project

Neural Network by David Christensen from the Noun Project

[9] Flowers by Made by Made from the Noun Project

Changi Airport by Keith Oh from the Noun Project

Sleep by Jae Deasigner from the Noun Project

Hugs by Gan Khoon Lay from the Noun Project

Relaxing by Phạm Thanh Lộc from the Noun Project

Job by Adrien Coquet from the Noun Project

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References

[menti]

[7]

[8]

[9]

Departure Data Set Analysis

- Main reasons for data loss:
  - **Flt**: missing data *(asrt, take-off not recorded, corrupted input data)*
  - **Astra**: inseparable tracks *(duplicate inbound and outbound name)*, unidentifiable start of taxi period *(taxi start outside red zone),* missing data *(corrupted input data)*
  - **Flt-Astra Join**: Astra contains indistinguishable ground vehicles tracks

Step	Departures
Schiphol Traffic Review *(2018/2019 Passenger & Full Freighter take-offs)*	498,145
Flt records *(flown, landplane, not local, general aviation filter)*	491,198
- With ASRT	487,890
Astra departure tracks***** *(latest runway entrance < latest red zone entrance, earliest runway exit $\nless$ earliest red zone entrance)*	457,305
Flt records matched with Astra (excl. runway check)	436,203
Flt records matched with Astra (incl. runway check)	436,045

***** Tracks of ground vehicles with radar can be indistinguishable from flights and therefore be included

Departure Prediction Data Set

- Predictions per horizon (TOBT or EOBT not null), missing matches

Horizon	0 min	30 min	2 hours	3 hours	Total
Predictions	436,125	435,213	426,413	287,318	1,585,069
Failed WFS match	0	2	2	2	6
Failed CFS match	2,389	5,822	31,439	52,372	92,022

  - Failed WFS match due to unique outliers (i.e. a flight where at 2/3h before asrt the flight is only expected to depart days later)
  - Failed CFS due to late publishing
  - 258 CFS double matches (multiple non identical matches for a prediction with no method for choosing the most applicable one)

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Departure Prediction Data Set

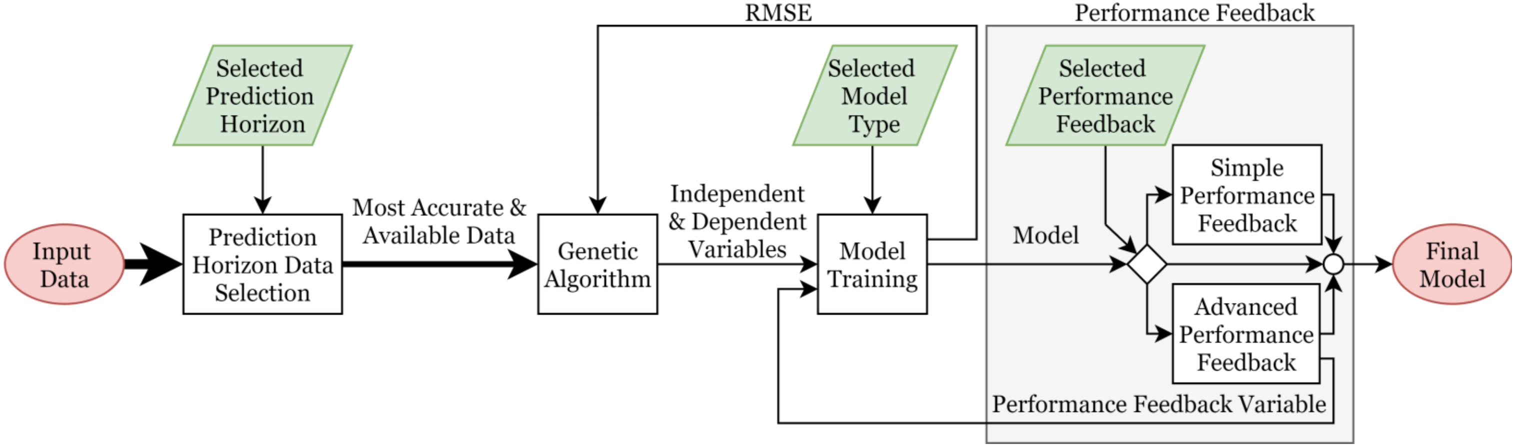
- Missing values per feature (others complete):

horizon	depgnr	sid	wind dir std	wind spd std	wind stoten	rvr5000 2000	other weather data	plr1	plr2	ptr1	ptr2	alr1	alr2	atr1	atr2
0	49	2573	54	54	177530	54	0	2389	313596	2490	169681	367717	399759	367818	411205
30	73	2503	57	57	177323	57	2	5822	312384	5935	171163	359659	398613	359772	403267
120	74	2012	3	3	173298	3	2	31439	320001	31564	176037	338567	392656	338692	379227
180	39	1289	2	2	111308	2	2	52372	227392	52528	132200	232533	267286	232689	256531
total	235	8377	116	116	639459	116	6	92022	1173373	92517	649081	1298476	1458314	1298971	1450230

  - Missing ‘wind stoten’ when <5 knts of wind spd
  - Missing plr1 corresponds to failed CFS match, secondary, alternative, or take-off runways are not permanently resulting in missing values.

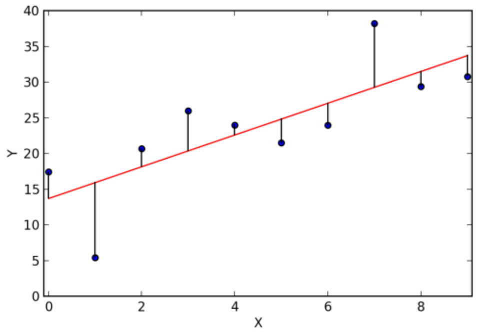
Modelling

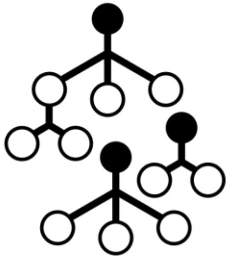
Content

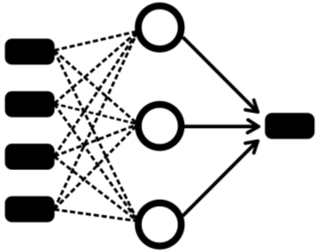


Methodology

- Modelling
  - Select Modelling Type
    - Linear Regression
    - Random Forest
    - Neural Network



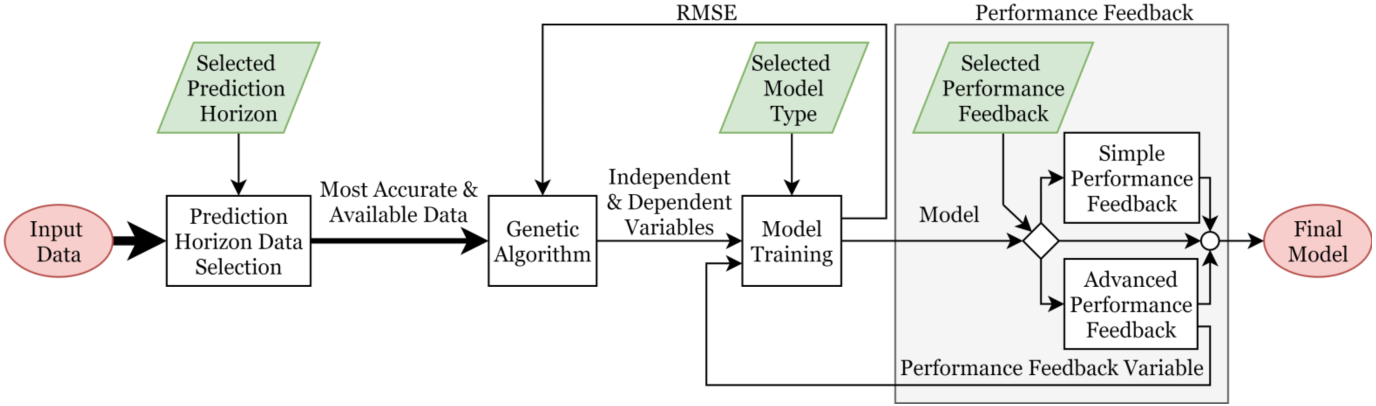




[7]

Methodology

- Modelling



Methodology

- Modelling
  - Performance Feedback
    using recent model performance to enhance adaptability of the model
    - Simple: add a fraction of the average error to the result
    - Advanced: train a second model with the error of the first model as additional input

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Recommendation

- Add a check for radar contact lost for <x seconds.

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Taxi Time Prediction (Departure)

- (Time entering the take-off runway) – (Time of last red zone exit)
- Data Sources:
  - Astra
  - Flt
  - Skv
  - CFS

Name	Use	Source	Comment
flt_sep_id	meta, id	flt, constructed	A constructed flight ID for flt entries grouped by sfplid, acid seperated when at least eight hours of seperation between entries with equal acid, sfplid
flt_range	meta, construction	flt, constructed	The time range of flt entries with the same flt_sep_id
final_trwy	meta, verification	flt, constructed	Take-off runway at the last flt entry of the flt_sep_id
t0_predict	meta, construction	flt, constructed	The maximum (last) asrt of flt entries with the same flt_sep_id
f_id_sep	meta, id	astra, constructed	A constructed flight ID from astra entries grouped by f_id seperated when at least half an hours of separation between entries with equal f_id
t_taxi	y	astra, constructed	Time of last entry of a runway polygon while not in flight - Time of last red zone polygon exit
type	meta, verification	astra, constructed	Identified type of flight (departure of arrival), used for verification
rwy	meta, verification	astra, constructed	Identified take-off or landing runway, used for verification (should be equal to final_trwy)
red_zone	meta	astra, constructed	Identified red zone (not used)
s_missed_rwy	meta, filter	astra, constructed	Amount of potentially missed seconds at the runway

Name	Use	Source	Comment
s_missed_red_zone	meta, filter	astra, constructed	Amount of potentially missed seconds at the red zone
t_spent	y	astra, constructed	Amount of time spent in each polygon, potential labels
horizon	meta, construction	model	The the between prediction and t0_predict (0, 30, 120, 180)
t_predict	timestamp	flt, model, constructed	The time of prediction (t0_predict + horizon)
trwy	cat	flt	Take-off runway
actype	cat, cardinal	flt	Aircraft type (icao designator)
obt_predict	timestamp	flt	Target off block time if available, else estimated off block time if available, else sobt
depgnr	cat	flt	Departure Gate Number
sid	cat	flt	Standard Instrument Departure
n_civil	num	flt, constructed	Number of civil aircraft with obt of at (slot if available else sobt) within 10 minutes of own obt
n_dep	num	flt, constructed	Number of departure non civil aircraft with obt within 10 minutes of own obt
n_arr	num	flt, constructed	Number of arrival non civil aircraft with at within 10 minutes of own obt

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Name	Use	Source	Comment
wtc	cat	icao	Wake Turbulence Category
rvr5000_1000	num	skv	"Kansen zicht < 5km en/of wolkenbasis < 1000 voet"
rvr1500_300	num	skv	"Kansen RVR < 1500 m en/of wolkenbasis < 300 voet"
rvr550_200	num	skv	"Kansen RVR < 550 m en/of wolkenbasis < 200 voet"
rvr350	num	skv	"Kansen RVR < 350 m"
rvrcat	cat	skv	"Prikwaarde zicht/wolkenbasis (klasse waarin mediaan zich bevindt: G= zicht ≥ 5km en wolkenbasis ≥ 1000 voet; M= Marginal VIS; A= fase A; B= fase B; C= fase C)"
wind_dir	cat, circular, bins 36	skv	Wind direction
wind_dir_std	num	skv	Standard deviation of wind direction
wind_spd	num	skv	Wind speed
wind_spd_std	num	skv	Standard deviation of wind speed
wind_stoten	num	skv	Wind gusts
temp	num	skv	Temperature
dew	num	skv	Dew Point
snow	num	skv	Probability of snow
snow_heavy	num	skv	Probability of medium/heavy snow
rain_cool	num	skv	Supercooled precipitation

Name	Use	Source	Comment
rain_cool	num	skv	Supercooled precipitation
cb	num	skv	Probability of CB
lightning	num	skv	Probability of lightning
rvr5000_2000	num	skv	"Kansen zicht < 5 km en/of wolkenbasis ≤ 2000 voet "
plr1	cat	cfs	Primary Landing Runway 1
plr2	cat	cfs	Primary Landing Runway 2
ptr1	cat	cfs	Primary Take-Off Runway 1
ptr2	cat	cfs	Primary Take-Off Runway 2
alr1	cat	cfs	Alternative Landing Runway 1
alr2	cat	cfs	Alternative Landing Runway 2
atr1	cat	cfs	Alternative Take-Off Runway 1
atr2	cat	cfs	Alternative Take-Off Runway 2
local_doy	cat circular bins 24	flt, constructed	Local day of year (0-365) of t_predict
local_dow	cat	flt, constructed	Local day of week (0-6) of t_predict
local_mod	cat circular bins 48	flt, constructed	Local minute of the day (0-24*60*60) of t_predict

Name	Use	Source	Comment
local_week	cat	flt, constructed	Local week of year (0-53?) of t_predict