Prediction of Flight Categories using LSTM Deep Learning

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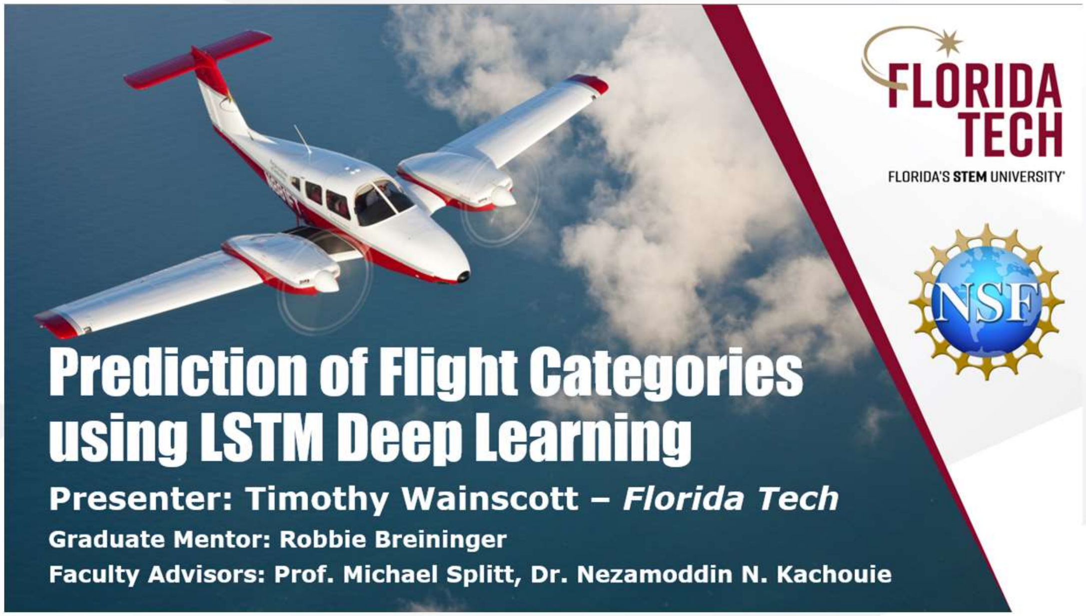
Table of Contents



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1. Introduction

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Weather Effects on Flight

Part 91 = GA = General Aviation – private and recreational flying in small aircraft
Part 135 = Commuter and on-demand flying (government, corporate, and helicopter operations)

Part 91 Weather-Related Accidents 2008-2022

	Weather-Related	Non-Weather Related	Total	Weather-Related Percentage
Accidents	4,341	15,197	19,538	22%
Fatal Accidents	990	2,586	3,576	28%

D.Eick / J.Thomas NTSB 2024

Eich, D. (2024, April). NTSB Weather Related Accidents. In *FPAW 2024 Spring Meeting*

Flight Rules

- Pilots operate under two different sets of procedures and practices while flying:

Visual Flight Rules (VFR) – primarily visual-based flying
– limited communication with ATC
– navigation is pilot-controlled

Instrument Flight Rules (IFR) – primarily instrument-based flying
– constant communication with ATC
– navigation is ATC-controlled

Flight Categories

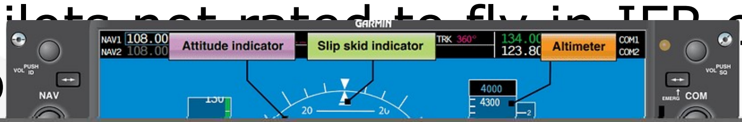
- Surface-based weather conditions divide flight rules into four flight categories (FCATs):
  - VFR, MVFR, IFR, LIFR

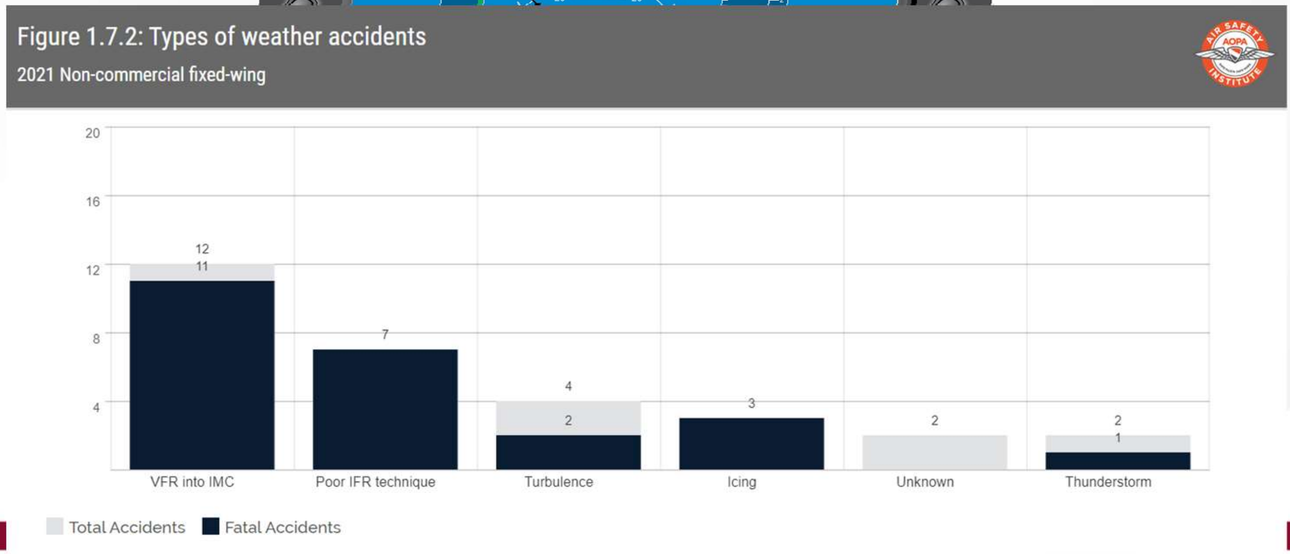
Category	Ceiling		Visibility
Visual Flight Rules VFR (green sky symbol)	greater than 3,000 feet AGL	and	greater than 5 miles
Marginal Visual Flight Rules MVFR (blue sky symbol)	1,000 to 3,000 feet AGL	and/or	3 to 5 miles
Instrument Flight Rules IFR (red sky symbol)	500 to below 1,000 feet AGL	and/or	1 mile to less than 3 miles
Low Instrument Flight Rules LIFR (magenta sky symbol)	below 500 feet AGL	and/or	less than 1 mile

https://www.faasafety.gov/gslac/alc/libview_printerfriendly.aspx?id=9091

Flight Rules

- Aircraft need to have certain instruments to be IFR certified
- Pilots need to be trained to be IFR certified
- Aircraft and/or pilots not rated to fly in IFR conditions (IMC) need to divert to





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How can we predict flight category if not already readily available?

Method 1 – Educated Guess

Applied Cognitive Psychology, Appl. Cognit. Psychol. **30**: 532–543 (2016)
Published online 8 April 2016 in Wiley Online Library (wileyonlinelibrary.com) **DOI**: 10.1002/acp.3225

Cognitive Biases in Visual Pilots' Weather-Related Decision Making

STEPHEN WALMSLEY and ANDREW GILBEY*

School of Aviation, Massey University, Palmerston North, New Zealand

- Pilots interpret weather differently based on previous information
- Pilots do not favor disconfirming evidence over confirming evidence
- Pilots would replicate a flight into IMC conditions if the outcome was favorable

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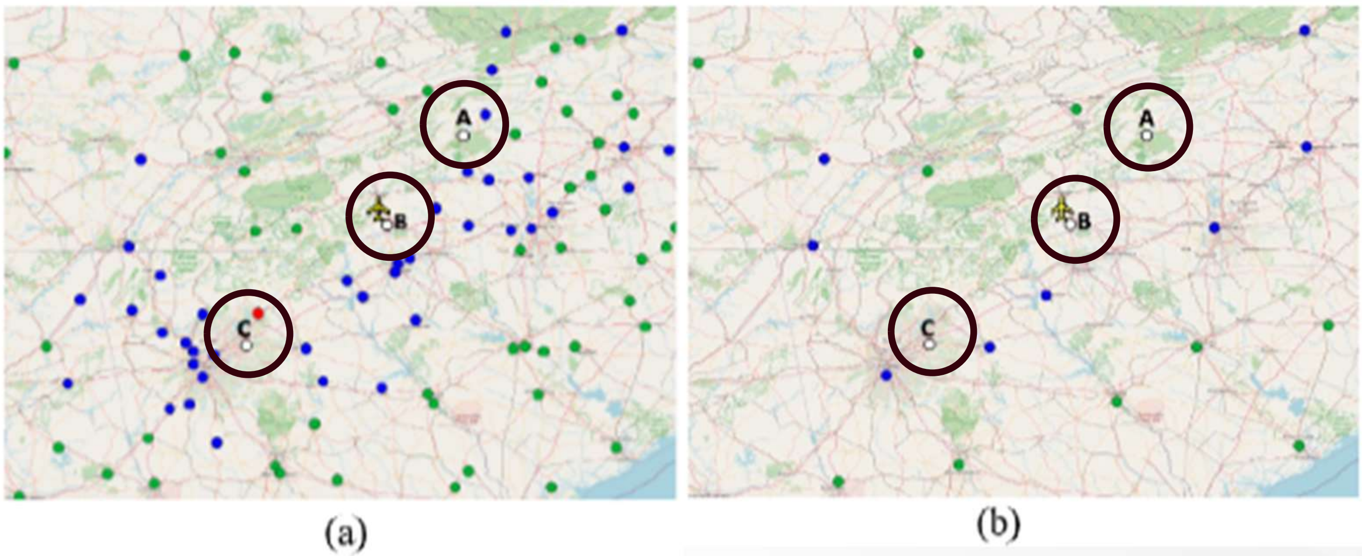
Method 1 – Educated Guess

Effects of Weather Information Observability and Uncertainty on Pilot Assessment of Weather Conditions and Decision Making

Barrett S. Caldwell, PhD[1,2], Michael E. Splitt, MA[3], and A. N. "Evv" Boerwinkle[1]
[1]School of Industrial Engineering, Purdue University, West Lafayette, IN
[2]School of Aeronautics and Astronautics, Purdue University, West Lafayette, IN
[3]College of Aeronautics, Florida Institute of Technology, Melbourne, FL



Location A	VFR	MVFR	IFR	LIFR
LOW OBS	14	10	0	0
MED OBS	23	1	0	0
HIGH OBS	0	23	1	0

Location B	VFR	MVFR	IFR	LIFR
LOW OBS	20	4	0	0
MED OBS	16	8	0	0
HIGH OBS	2	22	0	0

Location C	VFR	MVFR	IFR	LIFR
LOW OBS	21	3	0	0
MED OBS	3	17	3	1
HIGH OBS	0	11	13	0

Method 2 – Nearest Neighbor ("Dummy") Forecast

- See when a nearby station has a reported FCAT and see what are the chances that another station has the same FCAT

	Station 1	Station 2	VFR Count	VFR Percentage	IFR Count	IFR Percentage	Total Count
1	GEV	MKJ	5054	0.94	298	0.06	5352
2	GEV	VJI	5093	0.99	63	0.01	5156
3	GEV	JFZ	5282	0.97	144	0.03	5426
4	JFZ	MKJ	5663	0.96	265	0.04	5928
5	JFZ	VJI	5909	0.97	182	0.03	6091
6	JFZ	GEV	5282	0.97	144	0.03	5426
7	MKJ	JFZ	5663	0.96	265	0.04	5928
8	MKJ	GEV	5054	0.94	298	0.06	5352
9	MKJ	VJI	5524	0.96	222	0.04	5746
10	VJI	JFZ	5909	0.97	182	0.03	6091
11	VJI	GEV	5093	0.99	63	0.01	5156
12	VJI	MKJ	5524	0.96	222	0.04	5746

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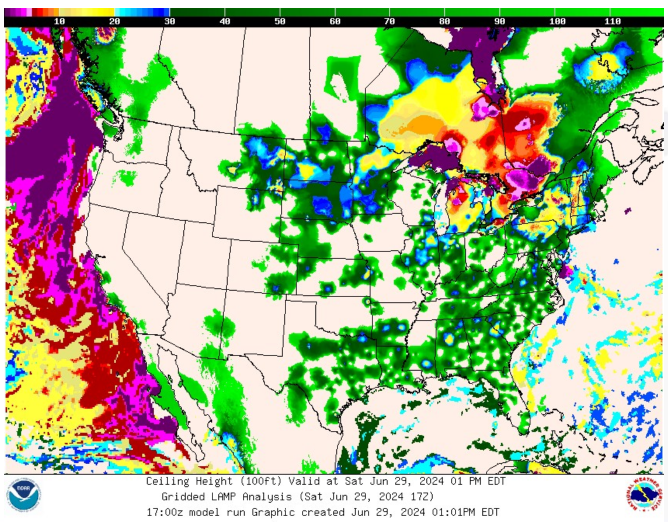
Method 3 – Numerically Predict Ceiling Height & Visibility

A Comparative Verification of Localized Aviation Model Output Statistics Program (LAMP) and Numerical Weather Prediction (NWP) Model Forecasts of Ceiling Height and Visibility

DAVID E. RUDACK AND JUDY E. GHIRARDELLI

Meteorological Development Laboratory, Office of Science and Technology, NOAA/NWS, Silver Spring, Maryland

(Manuscript received 18 November 2009, in final form 3 March 2010)



- Uses numeric models to predict ceiling height and visibility
- Accurate from 0 h future to 25 h future
- Is a complex way to solve our main research question

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Method 4 – Our Objective

Use Neural Networks to
Predict Flight Rules

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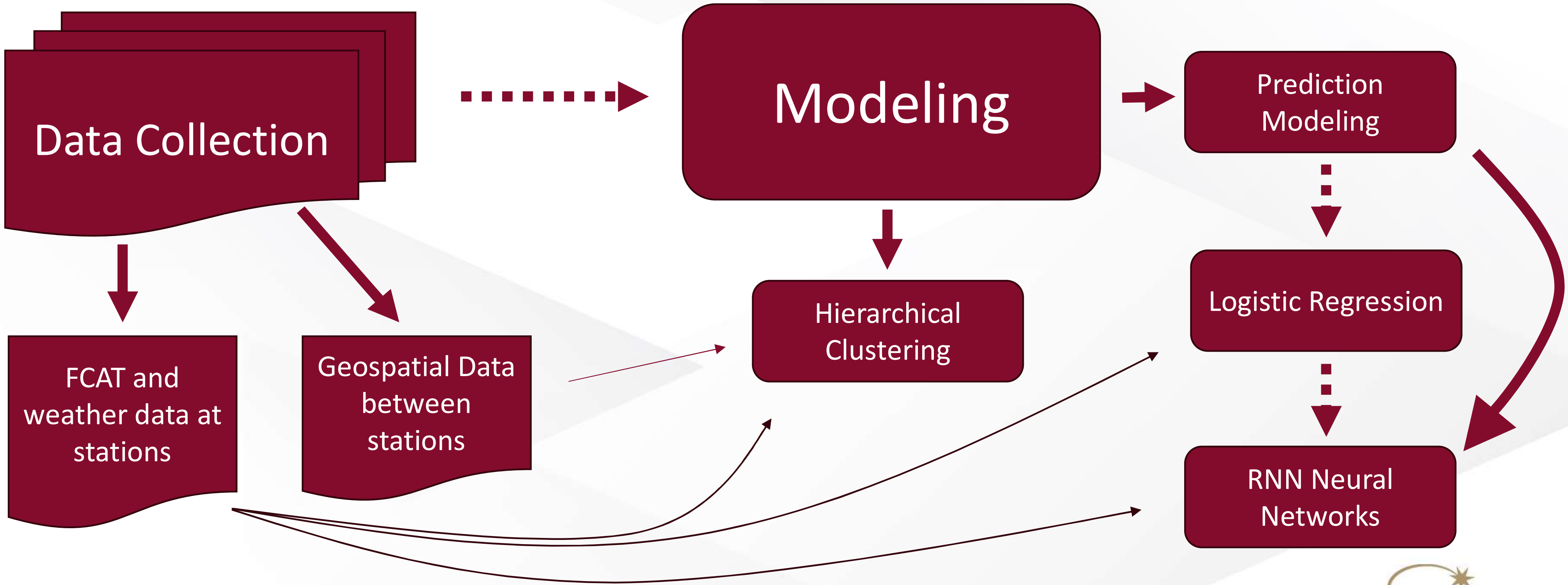
Method 4 – Our Objective

Use Neural Networks to Predict Flight Rules

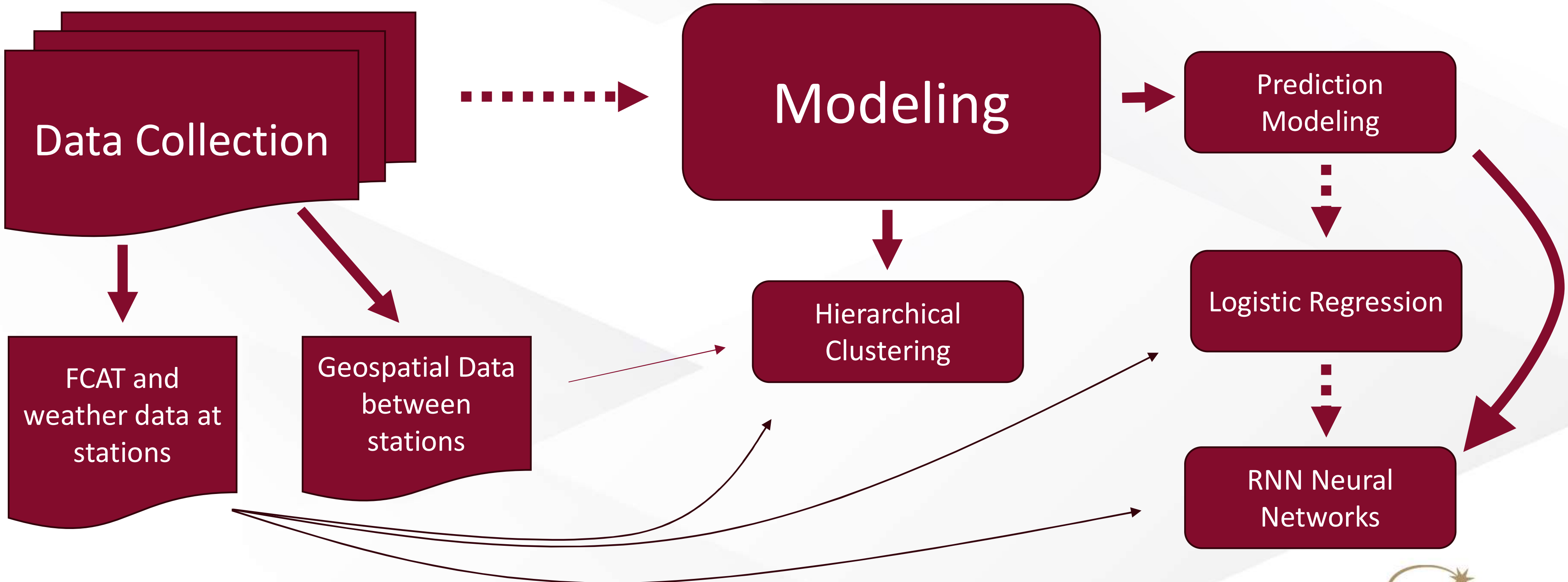
Hypothesis:

LSTM NNs will accurately predict Flight Categories

Schematics – Overall Work of REU



Schematics – Presented Work of REU

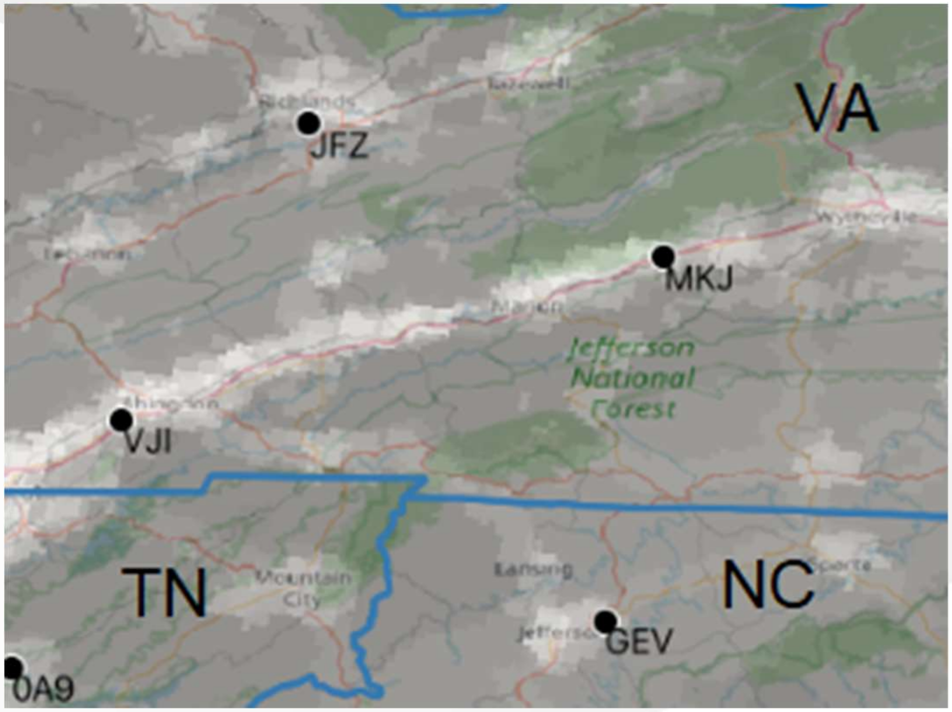


2. Data

Sample Size

- 194 total airports (stations) in the Appalachian region

- Neural network model uses 4 equidistant stations from sample



First Data Source

- AWOS/ASOS sites give hourly updates of weather including:
  - Visibility
  - Cloud Ceiling
  - Air Temperature
  - Dew Point
  - Relative Humidity
  - Wind Speed

- These will be our predictors for our prediction model

https://mesotech.com/pages/awos-3pt

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Neural Network Data

- For predictors, we use
  - FCATs (reported)
  - Air Temp (°C)
  - Dew Point (°C)
  - Relative Humidity (%)
  - and Wind Speed (kts)

> flight_data_more

	Station	Date	Time	CFCAT	VFCAT	FCAT	Air Temp	Dew Point	Rel Humid	Wind Speed
1	BCB	01/01/2019	01:00:00	MVFR	VFR	MVFR	15	13	88	5
2	BCB	01/01/2019	02:00:00	MVFR	VFR	MVFR	16	13	82	7
3	BCB	01/01/2019	03:00:00	MVFR	VFR	MVFR	17	14	82	5
4	BCB	01/01/2019	04:00:00	VFR	VFR	VFR	17	13	77	7
5	BCB	01/01/2019	05:00:00	VFR	VFR	VFR	17	13	77	8
6	BCB	01/01/2019	06:00:00	VFR	VFR	VFR	16	13	82	7
7	BCB	01/01/2019	07:00:00	VFR	VFR	VFR	15	13	88	6
8	BCB	01/01/2019	08:00:00	MVFR	VFR	MVFR	15	14	94	7
9	BCB	01/01/2019	10:00:00	VFR	VFR	VFR	13	11	88	6
10	BCB	01/01/2019	11:00:00	VFR	VFR	VFR	12	9	82	8
11	BCB	01/01/2019	12:00:00	VFR	VFR	VFR	12	8	76	5
12	BCB	01/01/2019	13:00:00	VFR	VFR	VFR	12	8	76	7
13	BCB	01/01/2019	14:00:00	VFR	VFR	VFR	12	8	76	4
14	BCB	01/01/2019	15:00:00	MVFR	VFR	MVFR	13	9	77	6

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Data Preparation – Neural Network

- Take FCATs of four stations and merge them according to date and timer
- Remove date, time, weather predictors (optional), and missing data

	FCAT JFZ	Date	Time	Temp (C)	Rel Humid	Wind Sp	FCAT MKJ	FCAT GEV	FCAT VJI
0	1	2020-03-01	1900-01-01 00:00:00	-3.0	54.0	3.0	1	1	1
1	1	2020-03-01	1900-01-01 01:00:00	-3.0	54.0	6.0	1	1	1
2	1	2020-03-01	1900-01-01 02:00:00	-3.0	54.0	6.0	1	1	1
3	1	2020-03-01	1900-01-01 03:00:00	-3.0	54.0	6.0	1	1	1
4	1	2020-03-01	1900-01-01 04:00:00	-3.0	54.0	5.0	1	1	1
6	1	2020-03-01	1900-01-01 05:00:00	-4.0	58.0	5.0	1	1	1
7	1	2020-03-01	1900-01-01 06:00:00	-4.0	58.0	4.0	1	1	1
8	1	2020-03-01	1900-01-01 07:00:00	-4.0	58.0	4.0	1	1	1
9	1	2020-03-01	1900-01-01 08:00:00	-4.0	58.0	3.0	1	1	1
10	1	2020-03-01	1900-01-01 09:00:00	-4.0	58.0	3.0	1	1	1
11	1	2020-03-01	1900-01-01 10:00:00	-4.0	58.0	0.0	1	1	1
12	1	2020-03-01	1900-01-01 11:00:00	-5.0	63.0	0.0	1	1	1

Data Preparation – Neural Network

- Separate response variable from predictor variable
- Split data sets into training and testing data sets

Response

Training

```
[1]
[1]
[1]
[1]
[1]
[1]
[1]
[1]
[1]
[1]
[1]
[1]
[1]
[1]
[1]
[1]
[1]
[1]
```

	FCAT JFZ
0	1
1	1
2	1
3	1
4	1
6	1
7	1
8	1
9	1
10	1
11	1
12	1

Testing

```
[1]
[1]
[1]
[1]
[1]
[1]
[0]
[1]
[1]
[0]
[1]
[0]
[1]
[1]
[1]
[1]
[1]
[1]
```

Predictors

Training

```
[[1. 0. 1.]]
[[1. 1. 1.]]
[[1. 1. 1.]]
[[1. 1. 1.]]
[[1. 1. 1.]]
[[1. 1. 1.]]
[[1. 1. 1.]]
[[1. 1. 1.]]
[[1. 1. 1.]]
```

FCAT MKJ	FCAT GEV	FCAT VJI
1	1	1
1	1	1
1	1	1
1	1	1
1	1	1
1	1	1
1	1	1
1	1	1
1	1	1
1	1	1
1	1	1
1	1	1

Testing

```
1.]]
1.]]
1.]]
1.]]
0.]]
1.]]
1.]]
1.]]
0.]]
```

Data Preparation – Neural Network

- Multiple questions as to how to format data for future work
  - Training-testing data split?
  - Date and time?
  - Missing data?
  - Weather predictors?
  - Geospatial/Cluster predictors?

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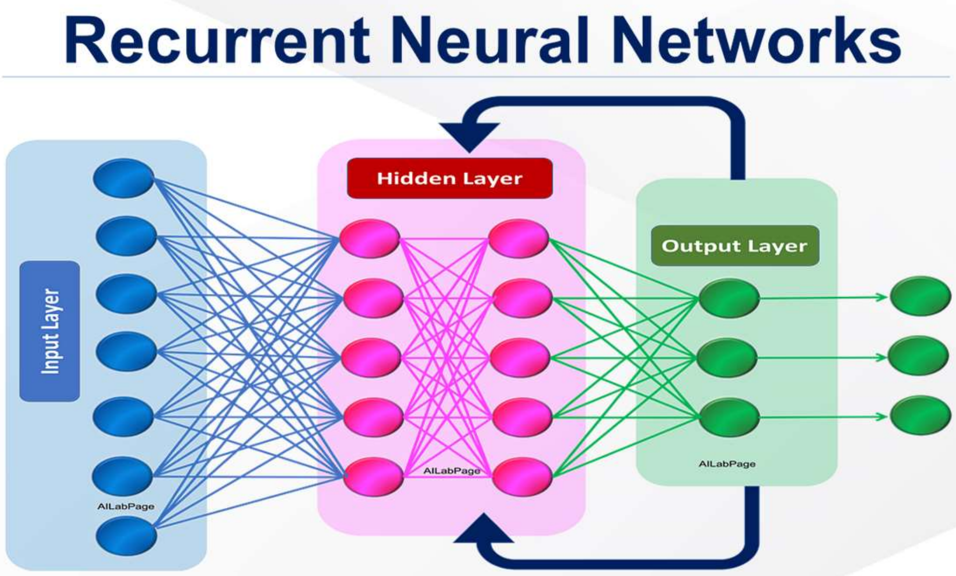
3. Methodology

Recurrent Neural Networks

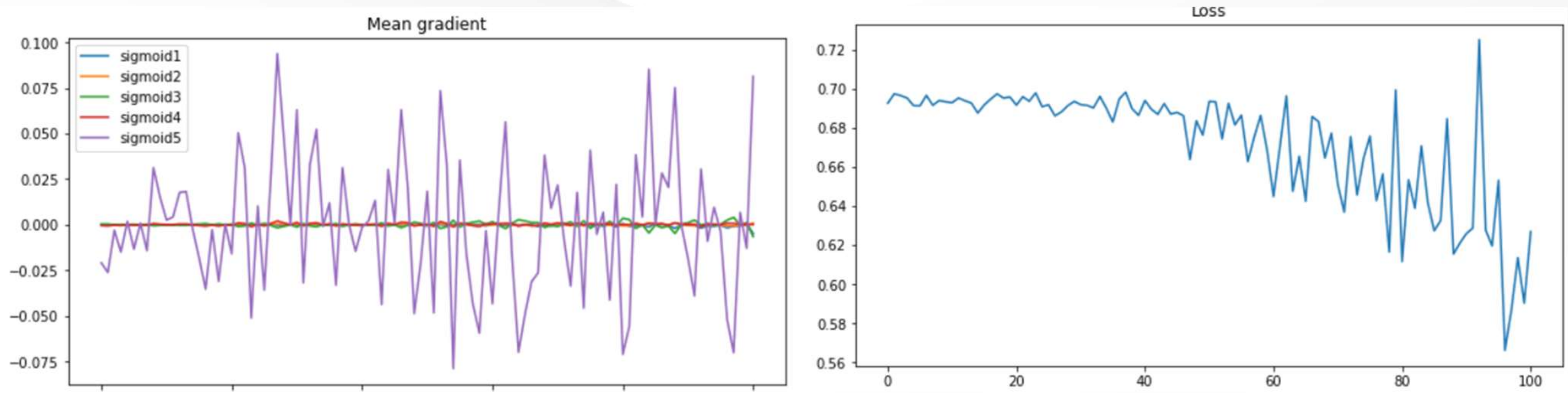
- Neural network that uses previous information in the next sequential data
- Commonly used in time series data
- Is the basis of our prediction model



Recurrent Neural Networks – Main Issue

- Difficult with large datasets

- Gradients (rate of change in loss) can either vanish or explode



https://machinelearningmastery.com/visualizing-the-vanishing-gradient-problem/

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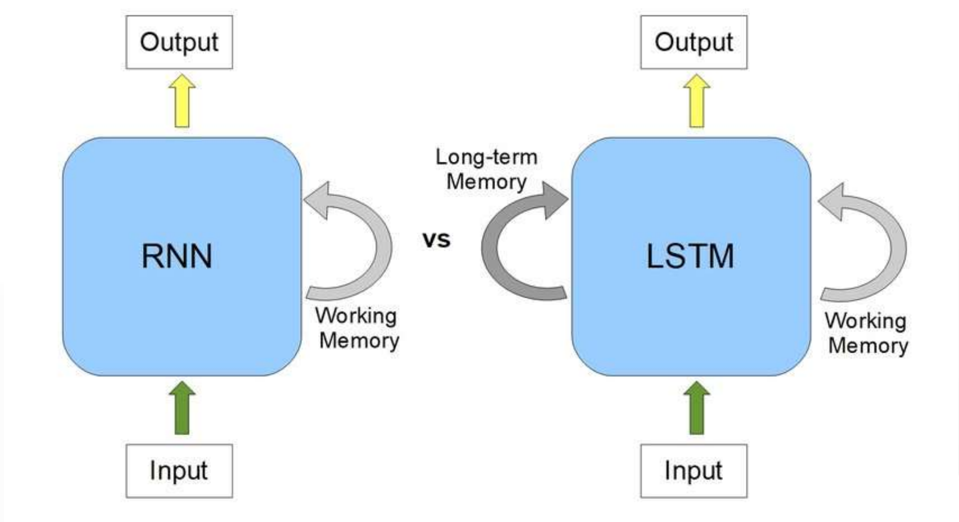
Long Short-Term Memory Neural Networks

- Solves the problem and exploding and vanishing gradients
- Uses gates to keep and forget certain information
- Can be made to go sequentially or bidirectionally

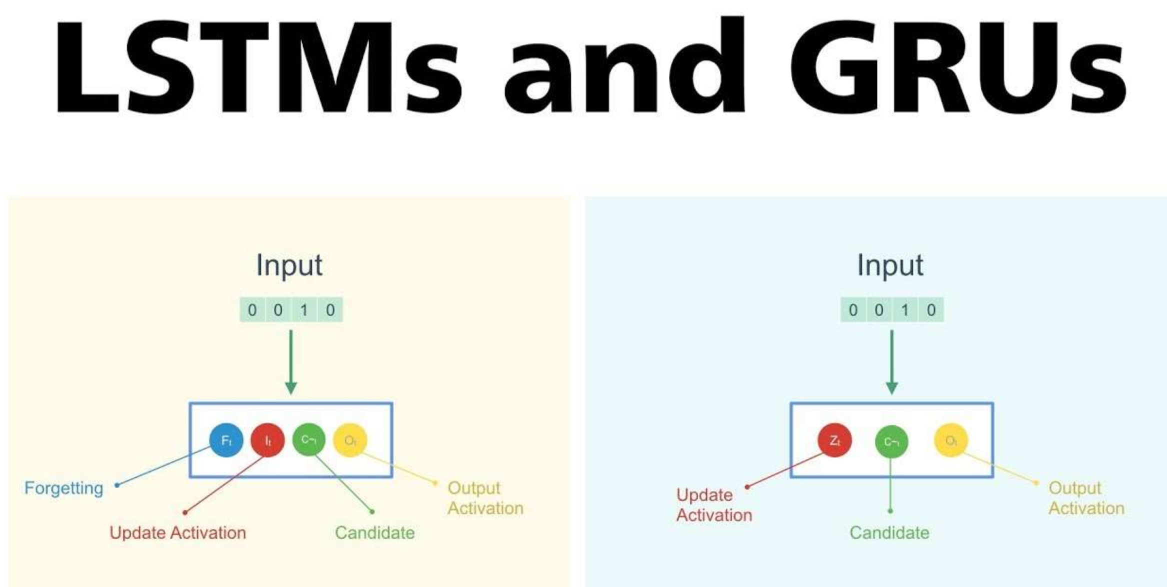


https://www.analyticsvidhya.com/blog/2022/01/the-complete-lstm-tutorial-with-implementation/

Gated Recurrent Units

- Also solves vanishing and exploding gradient problem

- Combines “forget” and “remember” gate in LSTM into one “update” gate



https://www.youtube.com/watch?app=desktop&v=4F69m3krMHw

4. Results

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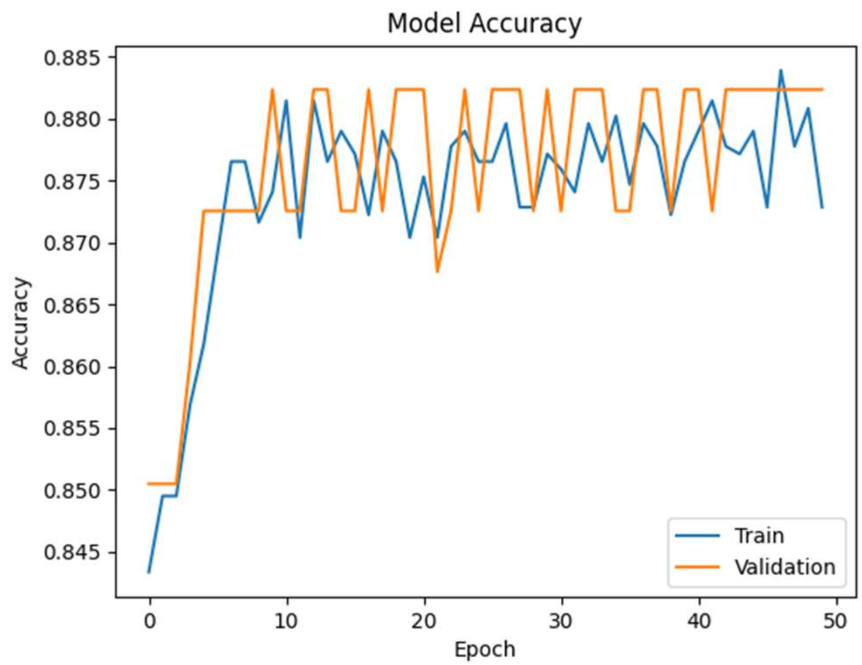
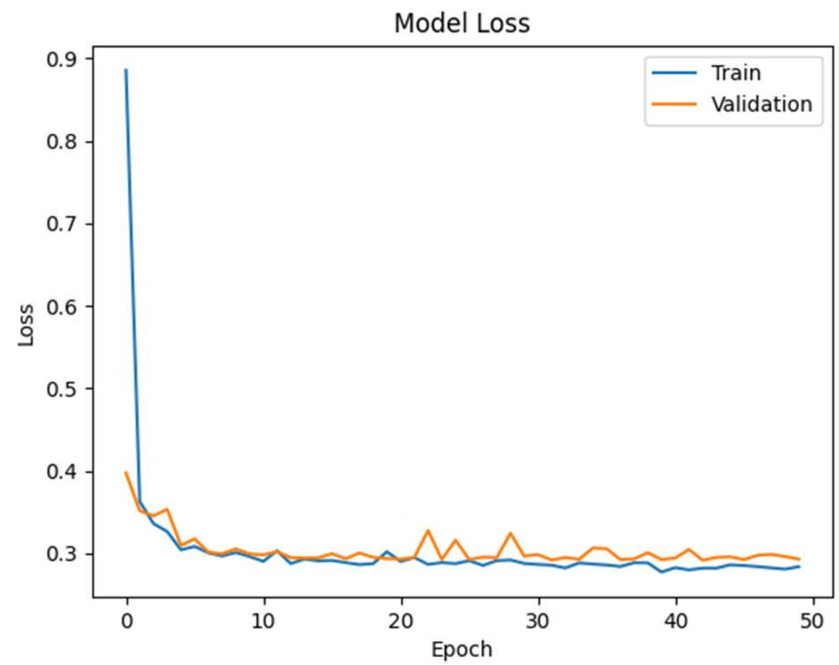
Results – LSTM: Binary





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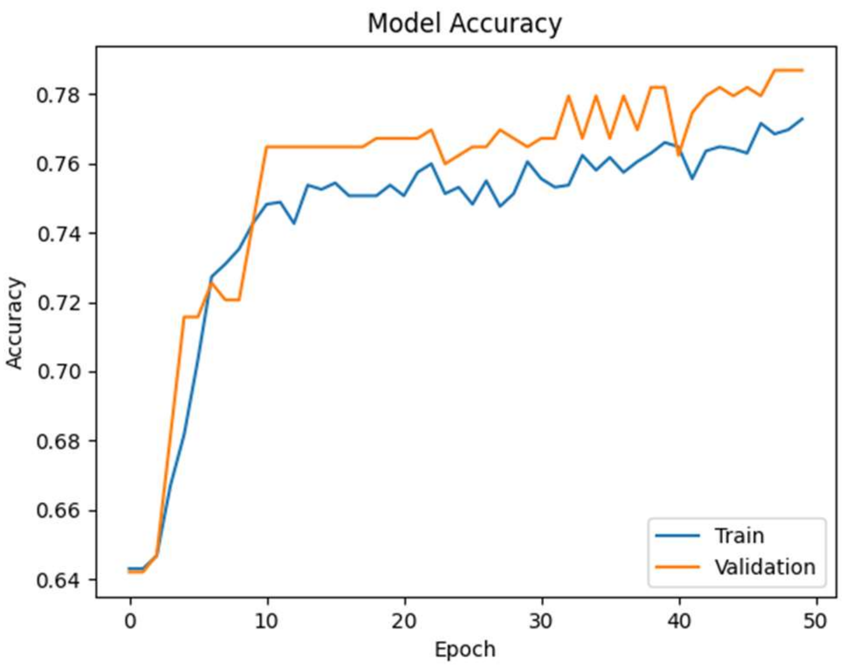
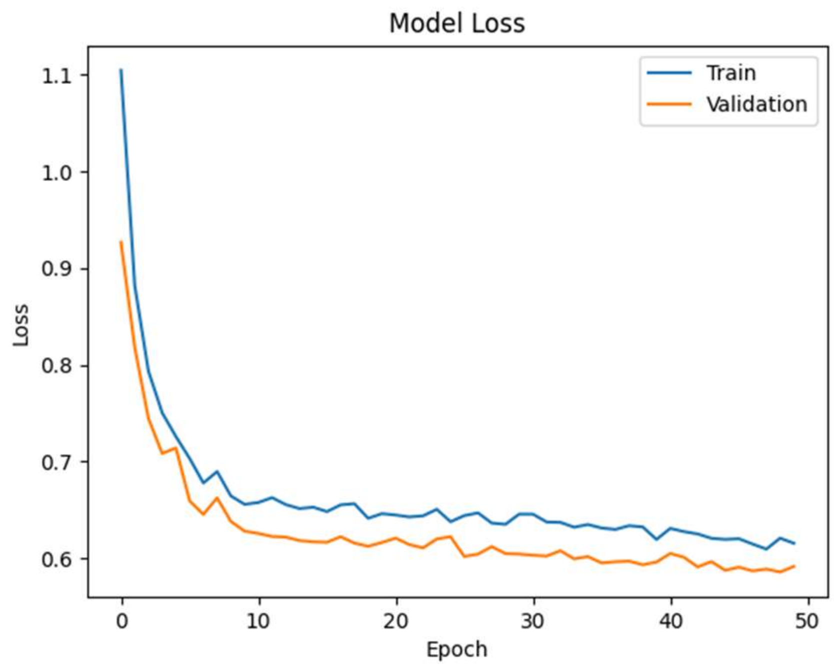
Results – LSTM: Multiclass





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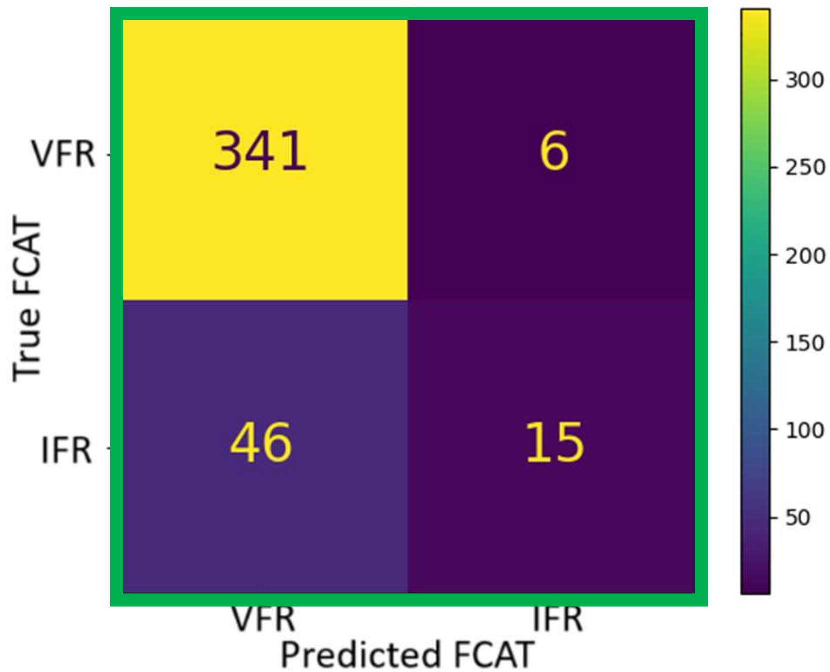
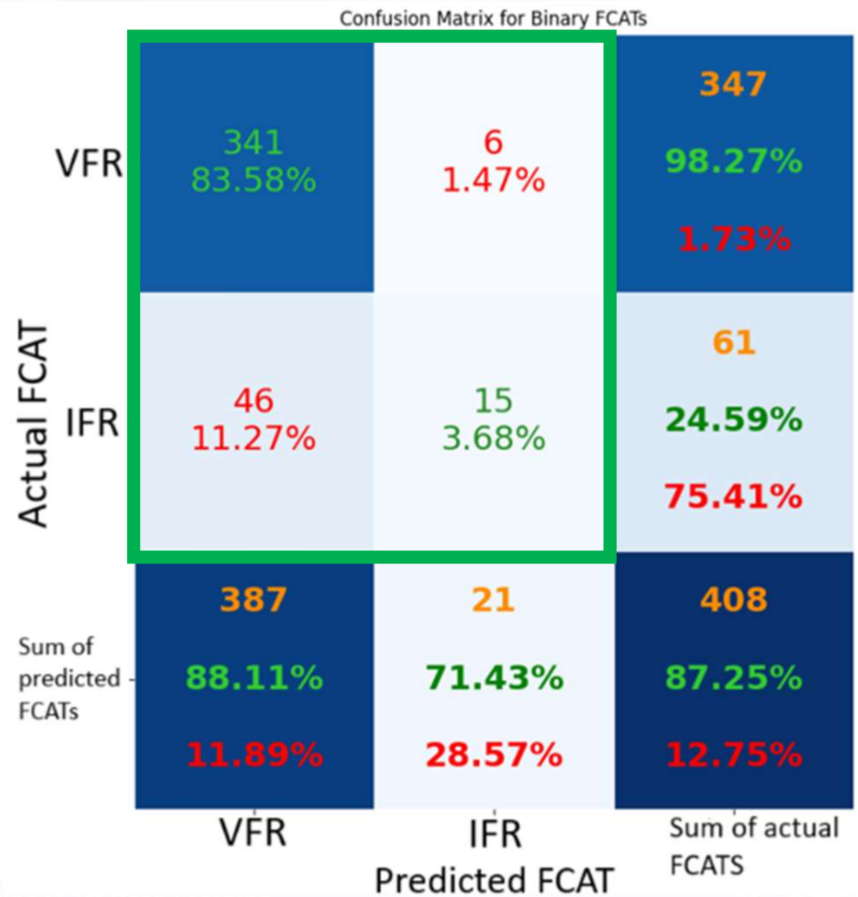
Confusion Matrices – LSTM: Binary

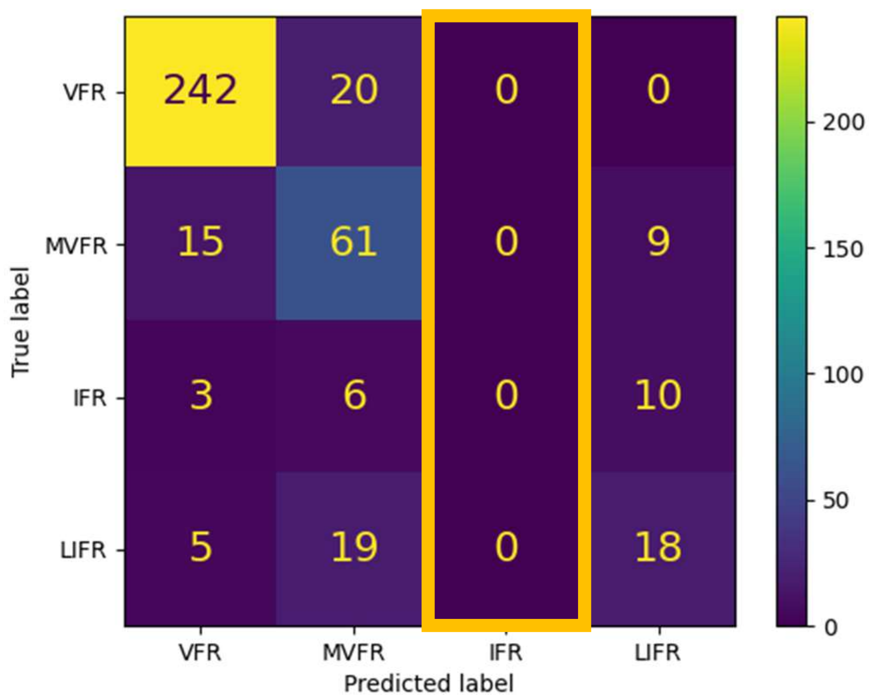


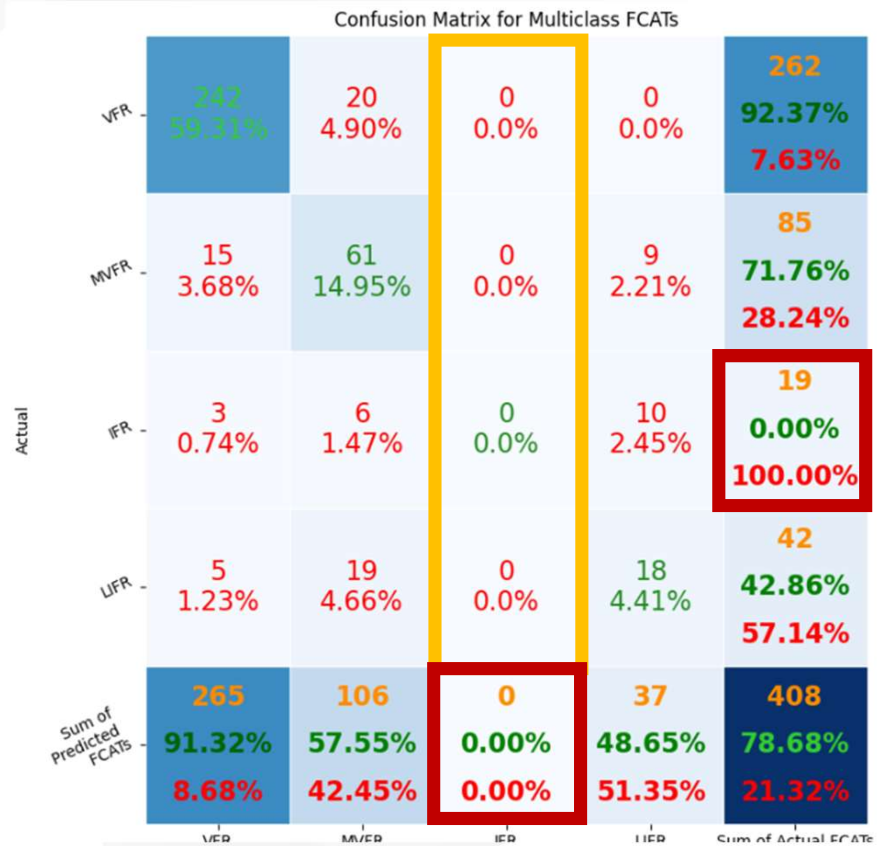


$$= \frac{341}{347} \cdot 100\%$$

$$= \frac{15}{61} \cdot 100\%$$

Confusion Matrices – LSTM: Multiclass





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Models	Accuracy (%)		Loss	
	MKJ	VJI	MKJ	VJI
RNN	86.06	93.35	0.3080	0.1828
GRU	85.96	93.43	0.3085	0.1823
LSTM	85.96	93.38	0.3081	0.1824

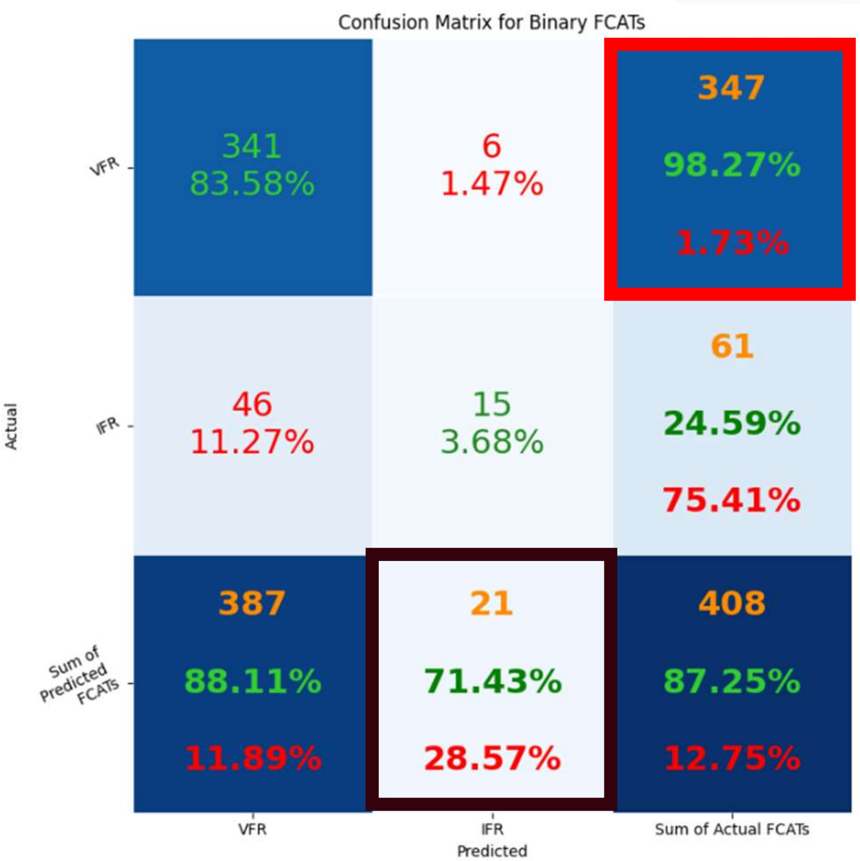
Table 13: Twenty-run average accuracy and loss for all stations (binary, 1 year data length)

Models	Accuracy (%)		Loss	
	MKJ	VJI	MKJ	VJI
RNN	74.60	83.29	0.6592	0.4683
GRU	74.96	83.34	0.6548	0.4651
LSTM	74.54	83.20	0.6570	0.4675

Table 14: Twenty-run average accuracy and loss for all stations (multi-class, 1 year data length)

FCAT	Models	Pos/Neg Prediction Accuracy (%)		True Pos/Neg Rate (%)	
		MKJ	VJI	MKJ	VJI
VFR	RNN	88.62	94.58	95.65	98.51
	GRU	89.61	94.50	93.95	98.39
	LSTM	88.70	94.43	95.38	98.74
IFR	RNN	65.53	65.42	38.17	32.22
	GRU	62.86	64.80	44.54	33.25
	LSTM	64.99	66.67	38.75	30.16

Table 15: Twenty-run average prediction and actual FCAT accuracy for all stations (binary, 1 year data length)



FCAT	Models	Pos/Neg Prediction Accuracy (%)		True Pos/Neg Rate (%)	
		MKJ	VJI	MKJ	VJI
VFR	RNN	88.62	94.58	95.65	98.51
	GRU	89.61	94.50	93.95	98.39
	LSTM	88.70	94.43	95.38	98.74
IFR	RNN	65.53	65.42	38.17	32.22
	GRU	62.86	64.80	44.54	33.25
	LSTM	64.99	66.67	38.75	30.16

Table 15: Twenty-run average prediction and actual FCAT accuracy for all stations (binary, 1 year data length)

FCAT	Models	Pos/Neg Prediction Accuracy (%)		True Pos/Neg Rate (%)	
		MKJ	VJI	MKJ	VJI
VFR	RNN	88.62	94.58	95.65	98.51
	GRU	89.61	94.50	93.95	98.39
	LSTM	88.70	94.43	95.38	98.74
IFR	RNN	65.53	65.42	38.17	32.22
	GRU	62.86	64.80	44.54	33.25
	LSTM	64.99	66.67	38.75	30.16

Table 15: Twenty-run average prediction and actual FCAT accuracy for all stations (binary, 1 year data length)

FCAT	Models	Pos/Neg Prediction Accuracy (%)		True Pos/Neg Accuracy (%)	
		MKJ	VJI	MKJ	VJI
VFR	RNN	83.07	90.66	94.42	94.62
	GRU	84.75	90.76	93.40	94.60
	LSTM	84.82	90.68	93.16	94.64
MVFR	RNN	63.74	62.54	50.57	58.35
	GRU	64.26	62.83	50.69	58.19
	LSTM	62.59	62.32	51.51	58.02
IFR	RNN	45.52	33.99	33.38	30.32
	GRU	40.88	39.07	40.60	39.22
	LSTM	39.15	39.67	40.07	36.51
LIFR	RNN	38.13	34.66	24.24	26.25
	GRU	35.70	38.05	26.00	23.51
	LSTM	38.03	36.21	21.29	23.75

Table 16: Twenty-run average prediction and actual FCAT accuracy for all stations (multi-class, 1 year data length)

Models	Accuracy (%)		Loss	
	MKJ	VJI	MKJ	VJI
RNN	86.06	93.35	0.3080	0.1828
GRU	– 0.10	+ 0.08	+ 0.0005	– 0.0005
LSTM	– 0.10	+ 0.03	+ 0.0001	– 0.0004

Table 17: Comparing accuracies and losses between RNN, GRU, and LSTM, with RNN as the baseline (binary, 1 year data length)

Models	Accuracy (%)		Loss	
	MKJ	VJI	MKJ	VJI
RNN	74.60	83.29	0.6592	0.4683
GRU	+ 0.36	+ 0.05	+ 0.0044	– 0.0032
LSTM	– 0.06	– 0.09	– 0.0022	– 0.0008

Table 18: Comparing accuracies and losses between RNN, GRU, and LSTM, with RNN as the baseline (multi-class, 1 year data length)

FCAT	Models	Pos/Neg Prediction Accuracy (%)		True Pos/Neg Rate (%)	
		MKJ	VJI	MKJ	VJI
VFR	RNN	88.62	94.58	95.65	98.51
	GRU	+ 0.99	+ 0.08	− 1.70	− 0.12
	LSTM	+ 0.08	− 0.15	− 0.27	+ 0.23
IFR	RNN	65.53	65.42	38.17	32.22
	GRU	− 2.67	− 0.62	+ 6.37	+ 1.03
	LSTM	− 0.54	+ 1.25	+ 0.58	− 2.06

Table 19: Comparing average prediction and actual FCAT accuracy for all stations between RNN, GRU, and LSTM, with RNN as the baseline (binary, 1 year data length)

FCAT	Models	Pos/Neg Prediction Accuracy (%)		True Pos/Neg Accuracy (%)	
		MKJ	VJI	MKJ	VJI
VFR	RNN	83.07	90.66	94.42	94.62
	GRU	+1.68	+0.10	−1.02	−0.02
	LSTM	+1.75	+0.02	−1.26	+0.02
MVFR	RNN	63.74	62.54	50.57	58.35
	GRU	+0.52	+0.29	−0.12	−0.16
	LSTM	+1.15	−0.24	+0.94	−0.33
IFR	RNN	45.52	33.99	33.38	30.32
	GRU	−4.64	+5.08	+7.22	+8.90
	LSTM	−6.37	+5.68	+6.69	+6.19
LIFR	RNN	38.13	34.66	24.24	26.25
	GRU	−2.40	+3.39	+1.76	−2.74
	LSTM	−0.10	+1.55	−2.95	−2.50

Table 20: Comparing average prediction and actual FCAT accuracy for all stations between RNN, GRU, and LSTM, with RNN as the baseline (multi-class, 1 year data length)

5. Conclusions

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Conclusions

- Binary has higher accuracy than multiclass, but loss doesn't decrease with validation data
- All three models have similar binary accuracy
- Models struggle with predicting rare events
- There are problems with certain stations having better/worse predictions than others

6. Future Work

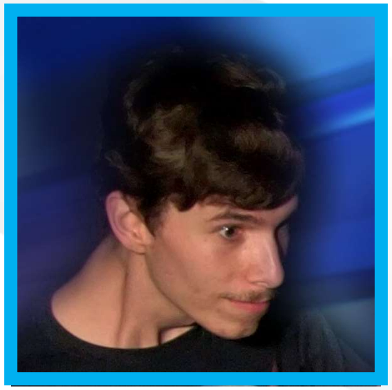
Future Work

- Continue to test our prediction model
  - Data splits
  - Different models
  - Predictors
  - Architecture

- Incorporate hierarchical clustering and/or geospatial data into our model

Research Team

(photo taken on Space Mountain at Disney World)



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Thanks!   Questions?

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Appendix

Methodology

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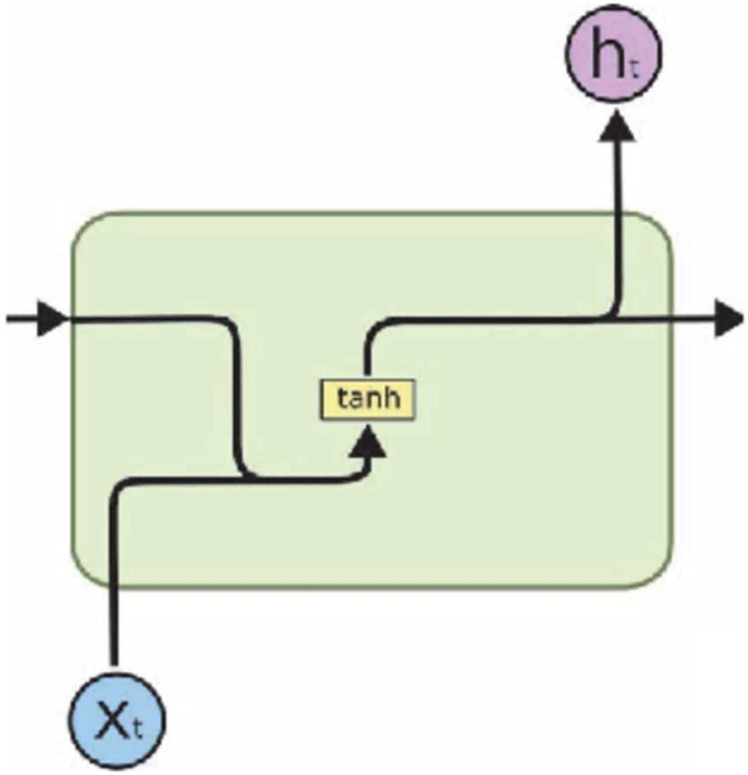
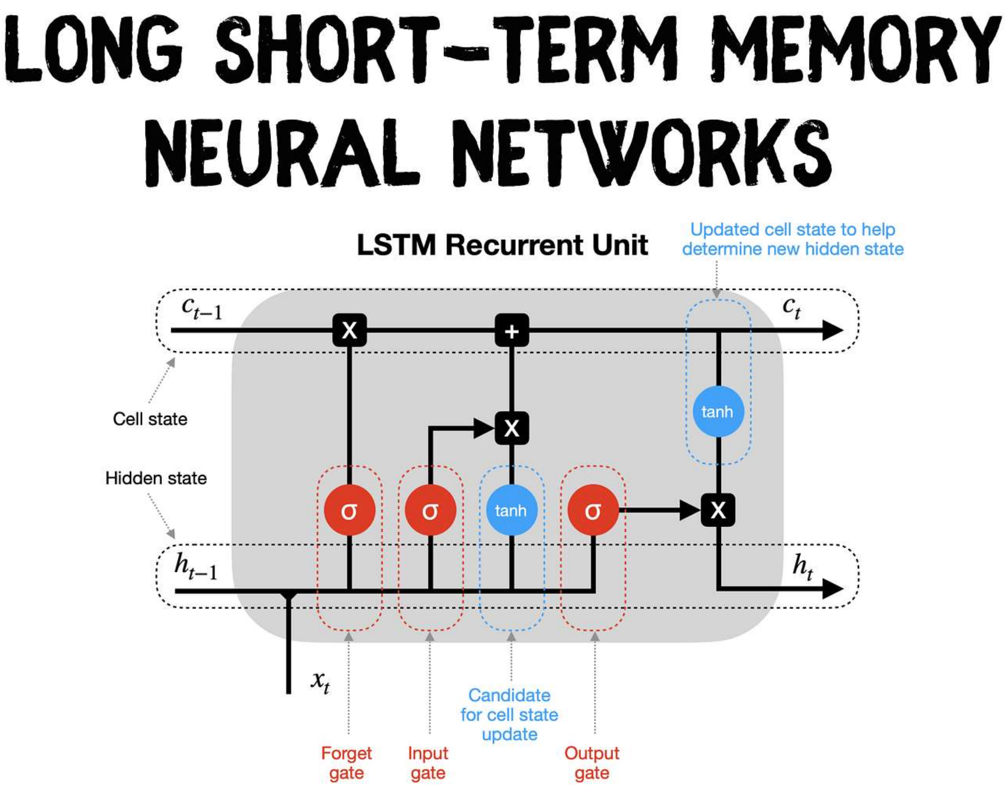
RNN Structure



https://towardsdatascience.com/grus-and-lstm-s-741709a9b9b1

LSTM Structure



https://towardsdatascience.com/lstm-recurrent-neural-networks-how-to-teach-a-network-to-remember-the-past-55e54c2ff22e

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GRU Structure

Results

Models	Accuracy (%)				Loss			
	MKJ	GEV	VJI	JFZ	MKJ	GEV	VJI	JFZ
RNN	86.06	86.61	93.35	86.78	0.3080	0.3653	0.1828	0.3574
GRU	85.96	86.60	93.43	86.78	0.3085	0.3654	0.1823	0.3582
LSTM	85.96	86.61	93.38	86.76	0.3081	0.3652	0.1824	0.3577

Table 5: Twenty-run average accuracy and loss for all stations (binary, 1 year data length)

Models	Accuracy (%)				Loss			
	MKJ	GEV	VJI	JFZ	MKJ	GEV	VJI	JFZ
RNN	74.60	69.81	83.29	75.07	0.6592	0.7902	0.4683	0.6936
GRU	74.96	69.80	83.34	74.91	0.6548	0.7893	0.4651	0.6915
LSTM	74.54	69.79	83.20	74.91	0.6570	0.7893	0.4675	0.6947

Table 6: Twenty-run average accuracy and loss for all stations (multi-class, 1 year data length)

FCAT	Models	Pos/Neg Prediction Accuracy (%)				True Pos/Neg Rate (%)			
		MKJ	GEV	VJI	JFZ	MKJ	GEV	VJI	JFZ
VFR	RNN	88.62	88.91	94.58	88.97	95.65	95.62	98.51	96.44
	GRU	89.61	89.00	94.50	89.05	93.95	95.55	98.39	96.27
	LSTM	88.70	89.00	94.43	89.01	95.38	95.55	98.74	96.36
IFR	RNN	65.53	68.50	65.42	60.54	38.17	44.39	32.22	31.12
	GRU	62.86	68.42	64.80	59.69	44.54	44.98	33.25	31.82
	LSTM	64.99	68.42	66.67	60.11	38.75	44.98	30.16	31.47

Table 7: Twenty-run average prediction and actual FCAT accuracy for all stations (binary, 1 year data length)

FCAT	Models	Pos/Neg Prediction Accuracy (%)				True Pos/Neg Accuracy (%)			
		MKJ	GEV	VJI	JFZ	MKJ	GEV	VJI	JFZ
VFR	RNN	83.07	79.91	90.66	83.15	94.42	85.10	94.62	94.81
	GRU	84.75	79.96	90.76	82.55	93.40	85.13	94.60	94.90
	LSTM	84.82	80.08	90.68	82.81	93.16	84.71	94.64	94.64
MVFR	RNN	63.74	42.92	62.54	45.05	50.57	37.99	58.35	36.58
	GRU	64.26	41.54	62.83	45.35	50.69	37.87	58.19	37.89
	LSTM	62.59	41.99	62.32	44.75	51.51	39.07	58.02	39.53
IFR	RNN	45.52	52.92	33.99	45.24	33.38	64.90	30.32	40.73
	GRU	40.88	53.62	39.07	47.76	40.60	63.82	39.22	38.01
	LSTM	39.15	53.58	39.67	48.43	40.07	64.36	36.51	37.13
LIFR	RNN	38.13	-	34.66	-	24.24	0.00	26.25	0.00
	GRU	35.70	-	38.05	1.82	26.00	0.00	23.51	2.04
	LSTM	38.03	-	36.21	-	21.29	0.00	23.75	0.00

Table 8: Twenty-run average prediction and actual FCAT accuracy for all stations (multi-class, 1 year data length)

Models	Accuracy (%)				Loss			
	MKJ	GEV	VJI	JFZ	MKJ	GEV	VJI	JFZ
RNN	86.06	86.61	93.35	86.78	0.3080	0.3653	0.1828	0.3574
GRU	− 0.10	− 0.01	+ 0.08	± 0.00	+ 0.0005	+ 0.0001	− 0.0005	+ 0.0008
LSTM	− 0.10	± 0.00	+ 0.03	− 0.02	+ 0.0001	− 0.0001	− 0.0004	+ 0.0003

Table 9: Comparing accuracies and losses between RNN, GRU, and LSTM, with RNN as the baseline (binary, 1 year data length)

Models	Accuracy (%)				Loss			
	MKJ	GEV	VJI	JFZ	MKJ	GEV	VJI	JFZ
RNN	74.60	69.81	83.29	75.07	0.6592	0.7902	0.4683	0.6936
GRU	+ 0.36	− 0.01	+ 0.05	− 0.16	+ 0.0044	− 0.0009	− 0.0032	+ 0.0021
LSTM	− 0.06	− 0.02	− 0.09	− 0.16	− 0.0022	− 0.0009	− 0.0008	+ 0.0011

Table 10: Comparing accuracies and losses between RNN, GRU, and LSTM, with RNN as the baseline (multi-class, 1 year data length)

FCAT	Models	Pos/Neg Prediction Accuracy (%)				True Pos/Neg Rate (%)			
		MKJ	GEV	VJI	JFZ	MKJ	GEV	VJI	JFZ
VFR	RNN	88.62	88.91	94.58	88.97	95.65	95.62	98.51	96.44
	GRU	+ 0.99	+ 0.09	+ 0.08	+ 0.08	− 1.70	− 0.07	− 0.12	− 0.14
	LSTM	+ 0.08	+ 0.09	− 0.15	+ 0.04	− 0.27	+ 0.07	+ 0.23	− 0.08
IFR	RNN	65.53	68.50	65.42	60.54	38.17	44.39	32.22	31.12
	GRU	− 2.67	− 0.08	− 0.62	− 0.85	+ 6.37	+ 0.59	+ 1.03	+ 0.70
	LSTM	− 0.54	− 0.08	+ 1.25	− 0.43	+ 0.58	+ 0.59	− 2.06	+ 0.35

Table 11: Comparing average prediction and actual FCAT accuracy for all stations between RNN, GRU, and LSTM, with RNN as the baseline (binary, 1 year data length)

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FCAT	Models	Pos/Neg Prediction Accuracy (%)				True Pos/Neg Accuracy (%)			
		MKJ	GEV	VJI	JFZ	MKJ	GEV	VJI	JFZ
VFR	RNN	83.07	79.91	90.66	83.15	94.42	85.10	94.62	94.81
	GRU	+1.68	+0.05	+0.10	−0.60	−1.02	+0.03	−0.02	+0.09
	LSTM	+1.75	+0.17	+0.02	−0.34	−1.26	−0.39	+0.02	−0.17
MVFR	RNN	63.74	42.92	62.54	45.05	50.57	37.99	58.35	36.58
	GRU	+0.52	−1.38	+0.29	+0.30	−0.12	−0.12	−0.16	+1.31
	LSTM	+1.15	−0.93	−0.24	−0.30	+0.94	+1.08	−0.33	+2.95
IFR	RNN	45.52	52.92	33.99	45.24	33.38	64.90	30.32	40.73
	GRU	−4.64	+0.70	+5.08	+2.52	+7.22	−1.08	+8.90	−2.72
	LSTM	−6.37	+0.66	+5.68	+3.19	+6.69	−0.54	+6.19	−3.60
LIFR	RNN	38.13	-	34.66	-	24.24	0.00	26.25	0.00
	GRU	−2.40	-	+3.39	+1.82	+1.76	±0.00	−2.74	+2.04
	LSTM	−0.10	-	+1.55	-	−2.95	±0.00	−2.50	±0.00

Table 12: Comparing average prediction and actual FCAT accuracy for all stations between RNN, GRU, and LSTM, with RNN as the baseline (multi-class, 1 year data length)

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