An aerial photograph of a winding asphalt road that curves through a dense, green forest on a mountain slope. The road is light-colored and contrasts with the dark green trees. The terrain is rugged, with some rocky patches visible. The overall scene is captured from a high angle, looking down at the road as it disappears into the forest.

Wildfire Cause Prediction with GNNs

Jimmy Howerton & Mark Tenzer

01

MOTIVATION

Why study wildfires?

02

DATA

Fires, Populations,
Weather

03

METHODS

Baselines, GCN,
GraphSAGE, GIN

04

PROGRESS

Data subset results

05

PLAN

Full dataset results,
comparisons, reasoning



Why Predict Wildfire Cause?

- Expense of wildfire cause evaluation
- Graphical Approach
- Data augmentation

KNOWN FACTORS



POPULATION

Arson and other human-caused fires usually occur near population centers.

ELEVATION

Lightning is much more likely at high elevations.

WEATHER

Naturally-caused fires, on average, require drier conditions.

Also, thunderstorms predict lightning fires.

WILDFIRES	ROWS	FEATURES
	1.88M	29

KAGGLE WILDFIRE DB

- All U.S. wildfires, 1992-2015
- Size, Discovery Date, Containment Date,
Location, etc.
- Cause

DATA

	ROWS	FEATURES
WILDFIRES	1.88M	29
POPULATION	141K	7

WORLD CITIES DATABASE

- Countries, Cities, Regions
- Location
- Population

DATA

	ROWS	FEATURES
WILDFIRES	1.88M	29
POPULATION	141K	7
WEATHER	1.56M	32

NOAA GSOD

- 1929-Present
- One reading per day per station
- Missed readings
- Snow, Hail, Wind, etc.
- Temperature, Thunder, Precipitation, Dew Point

MLP

- **3 Hidden dense layers**
 - **64 Neurons per layer**
 - **ReLU activation**
 - **Batch normalization**
- **dense 11-node softmax output**

BASELINE - MLP



BASELINE - MLP

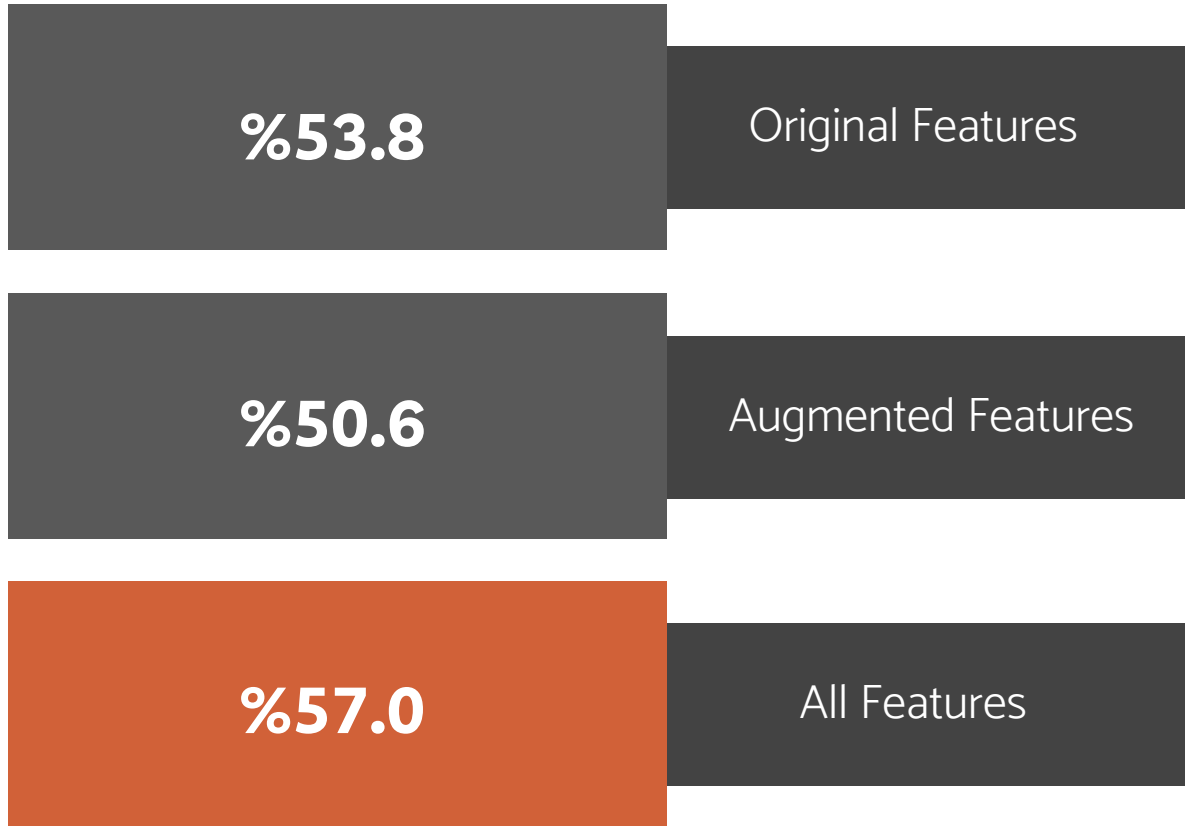
%53.8

Original Features

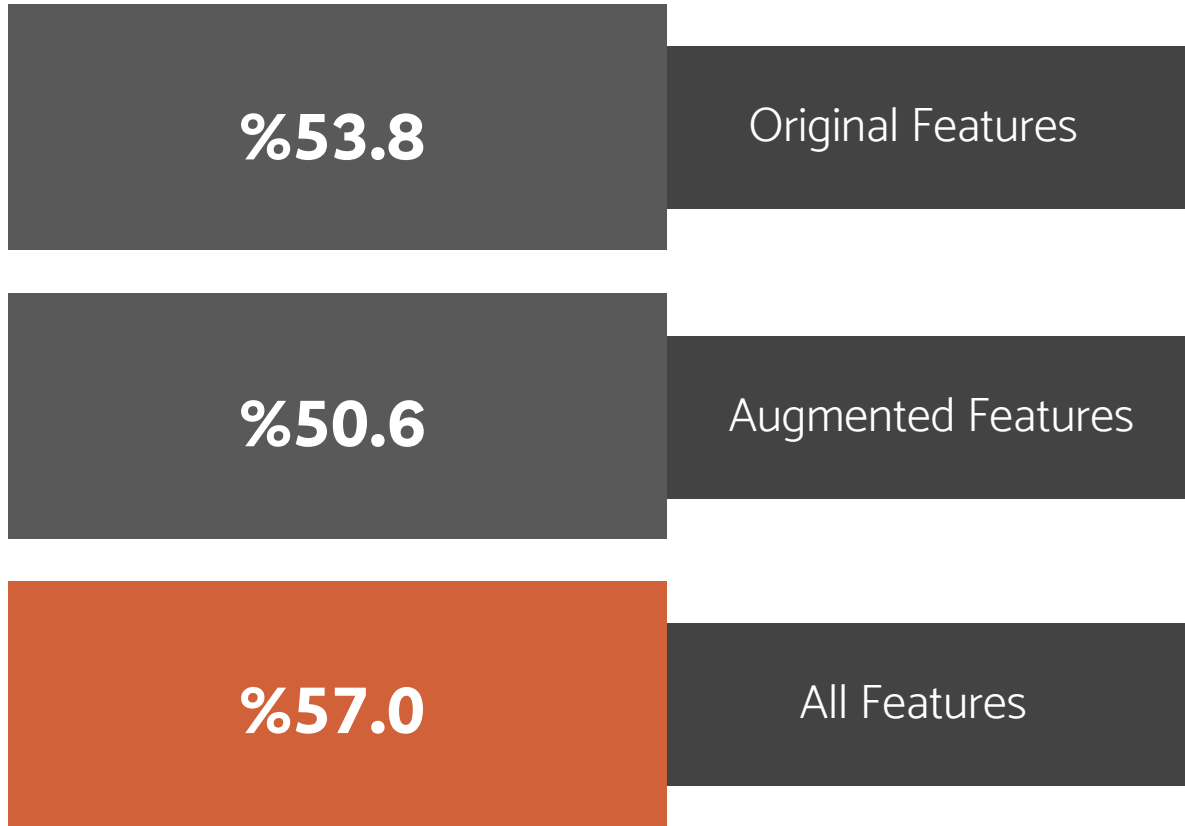
%50.6

Augmented Features

BASELINE - MLP

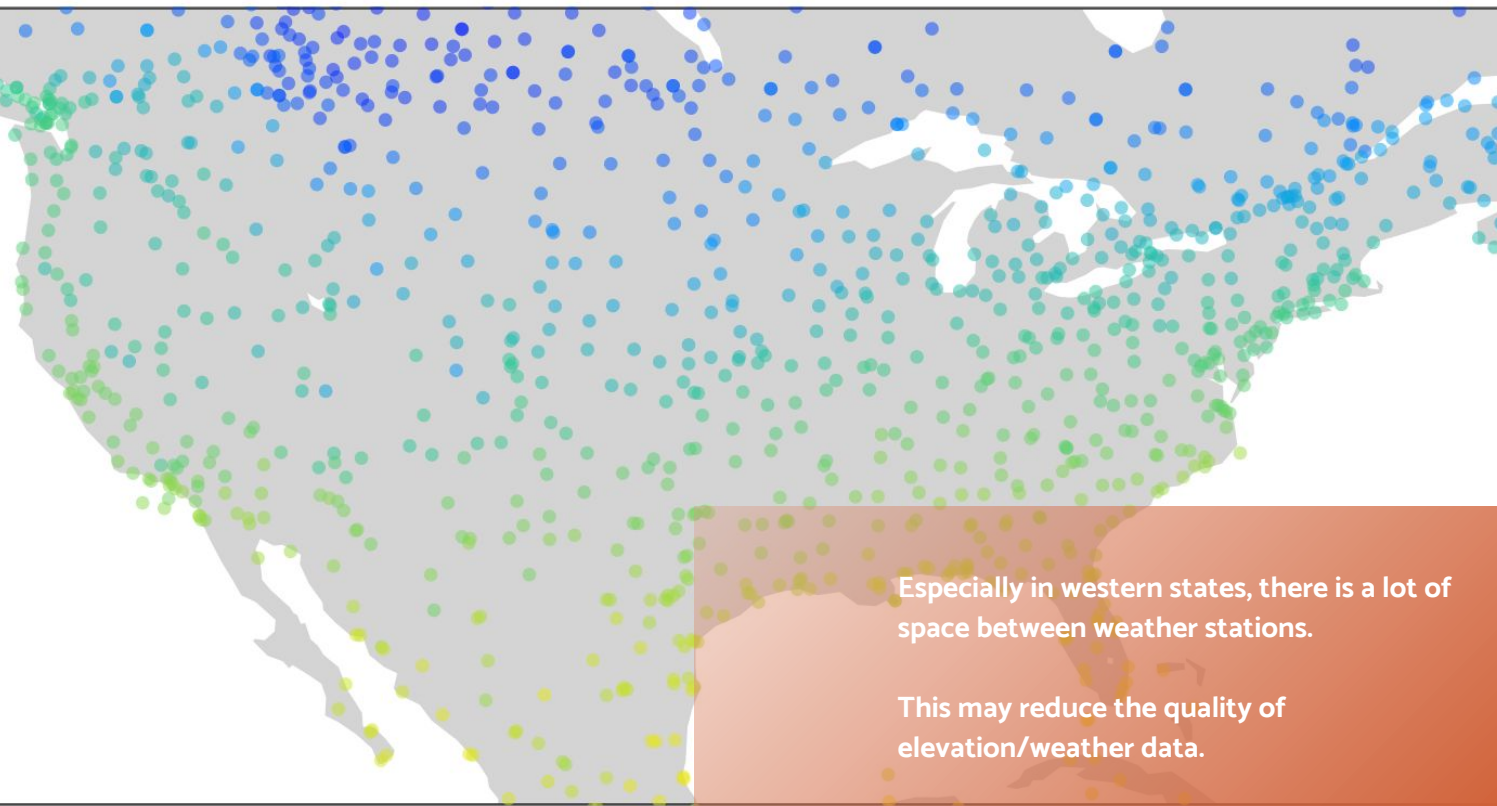


BASELINE - MLP



Kaggle
%58.0
(Random forest)

WHY?



CONNECTIONS



SPACE

Connect fires by
latitude &
longitude

METHODS

CONNECTIONS



SPACE

Connect fires by
latitude &
longitude



TIME

Connect fires by day of
year occurred

CONNECTIONS



SPACE

Connect fires by
latitude &
longitude



TIME

Connect fires by day of
year occurred



SPACE + TIME

Connect fires by
both latitude,
longitude, and day
of year

METHODS

CONNECTIONS



SPACE

Connect fires by
latitude &
longitude



TIME

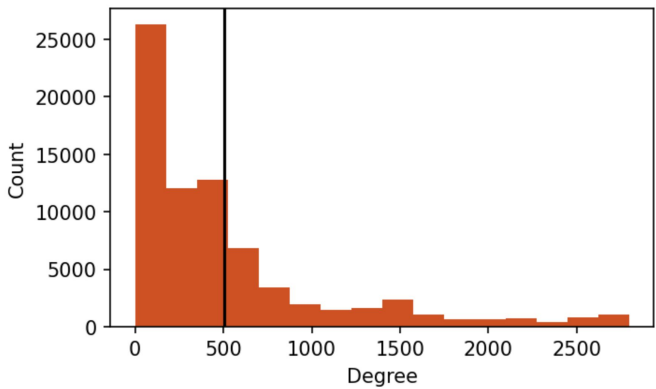
Connect fires by day of
year occurred



SPACE + TIME

Connect fires by
both latitude,
longitude, and day
of year

Degree distribution for A_{space}
 $c = 507.4$



CONNECTIONS



SPACE

Connect fires by
latitude &
longitude



TIME

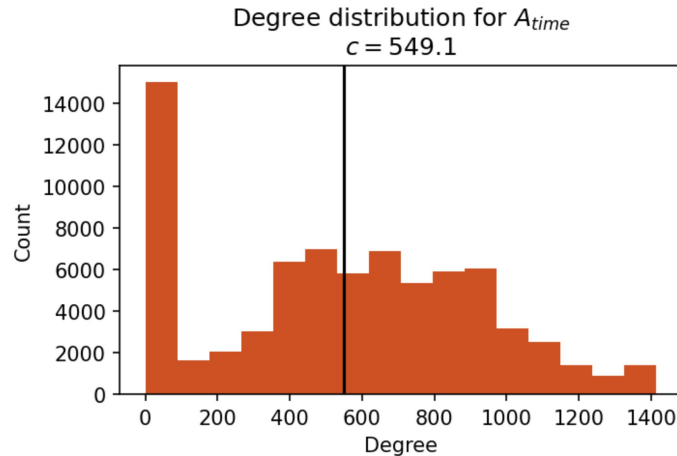
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METHODS



CONNECTIONS



SPACE

Connect fires by
latitude &
longitude



TIME

Connect fires by day of
year occurred

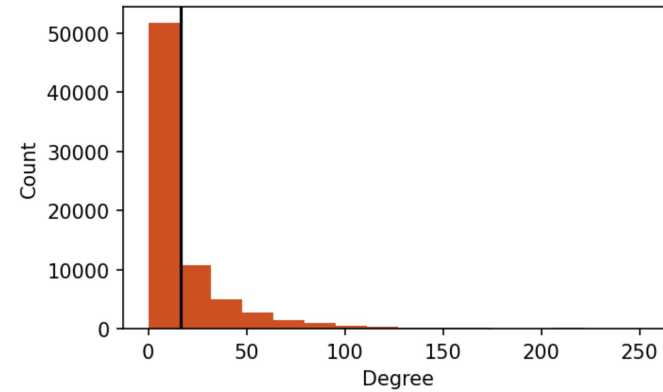


SPACE + TIME

Connect fires by
both latitude,
longitude, and day
of year

METHODS

Degree distribution for A_{both}
 $c = 16.7$



CONNECTIONS



SPACE

Connect fires by
latitude &
longitude



TIME

Connect fires by day of
year occurred



SPACE + TIME

Connect fires by
both latitude,
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of year

MODELS



GCN

Mean Pooling

CONNECTIONS



SPACE

Connect fires by
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SPACE + TIME

Connect fires by
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MODELS



GCN

Mean Pooling



GraphSAGE

Max Pooling

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SPACE + TIME

Connect fires by
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MODELS



GCN

Mean Pooling



GraphSAGE

Max Pooling



GIN

Sum Pooling
MLP: 1 hidden layer, 64 neurons

CONNECTIONS



SPACE

Connect fires by
latitude &
longitude



TIME

Connect fires by day of
year occurred



SPACE + TIME

Connect fires by
both latitude,
longitude, and day
of year

MODELS - DNN Variant



GCN

Mean Pooling



GraphSAGE

Max Pooling



GIN

Sum Pooling
MLP: 1 hidden layer, 64 neurons



- Python library for graph deep learning
- based on Keras and Tensorflow
- all models run on GPU in Ubuntu
- Implements **GCN**, **GraphSAGE**, and **GIN** into Keras model layers

MODEL SPECS

5

GNN Layers

500

Epochs

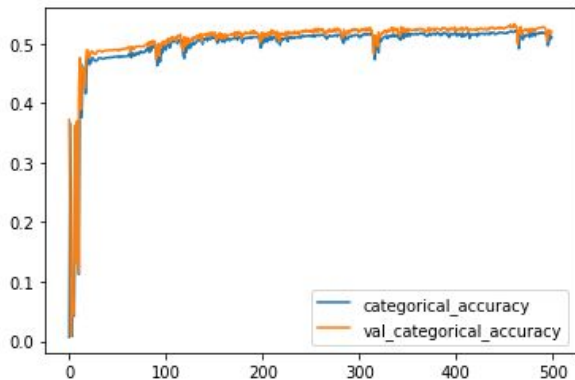
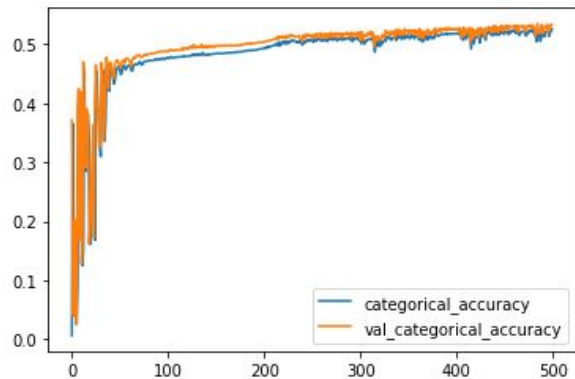
3

DNN Layers

Mean

Imputation

SPACE + TIME (2015)



GCN

Converges quickly, but performs worse than a simple fully-connected model

~53.4%



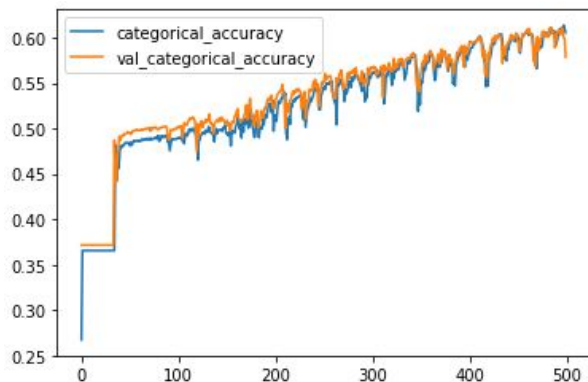
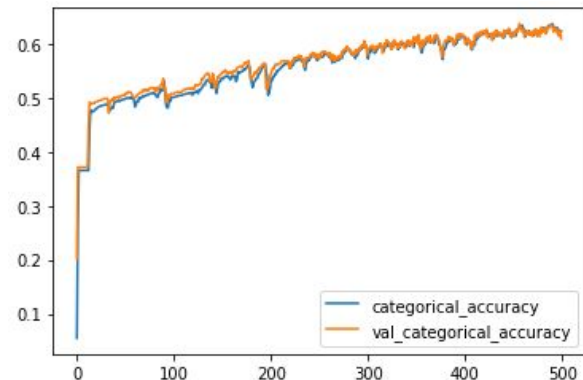
GCN-DNN

Adding the fully-connected model, with the node embedding as input, does not improve performance

~52.0%

PROGRESS - GCN

SPACE + TIME (2015)



GraphSAGE

Achieves state-of-the-art performance!

~63.0%



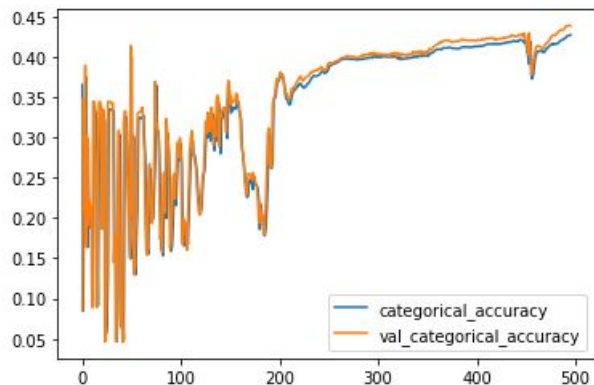
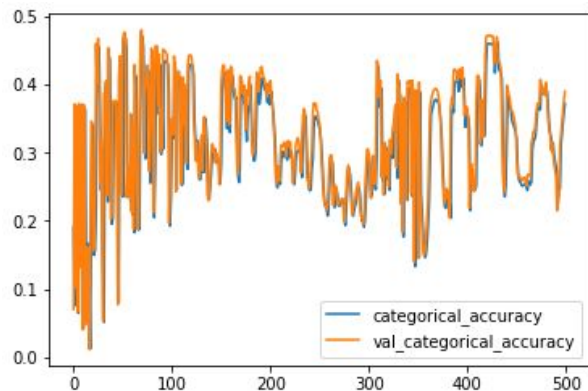
GraphSAGE-DNN

Also outperforms the baseline, but the added DNN does not improve the model.

~61.0%

PROGRESS - GraphSAGE

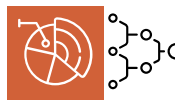
SPACE + TIME (2015)



GIN

GIN struggles to converge after even 500 epochs of training.

~ ?



GIN-DNN

The addition of a DNN stabilizes the training, but overall accuracy still is poor.

~43.0%

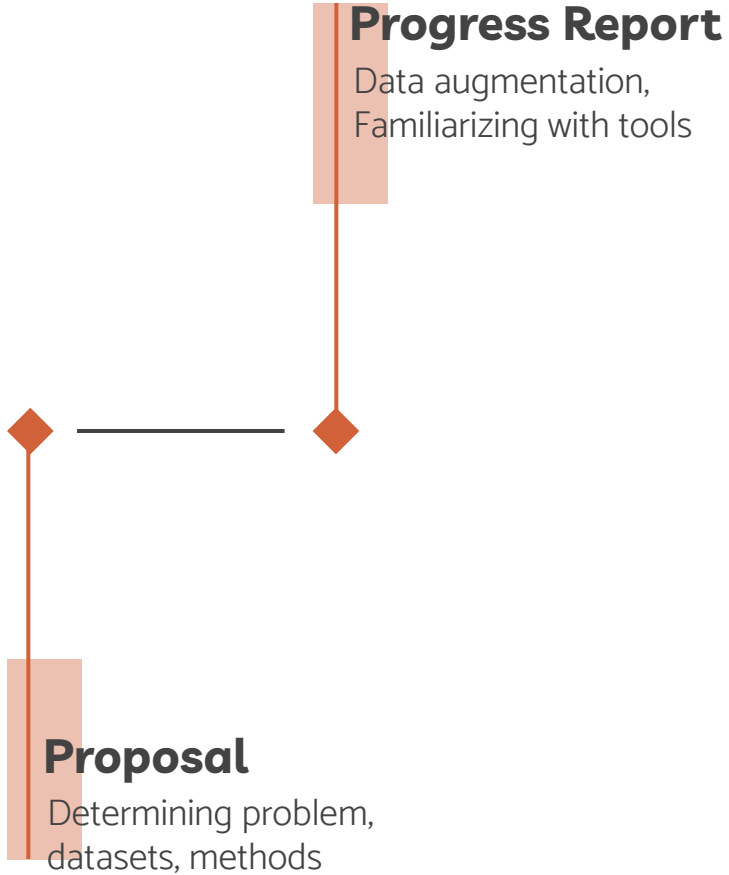
PROGRESS - GIN

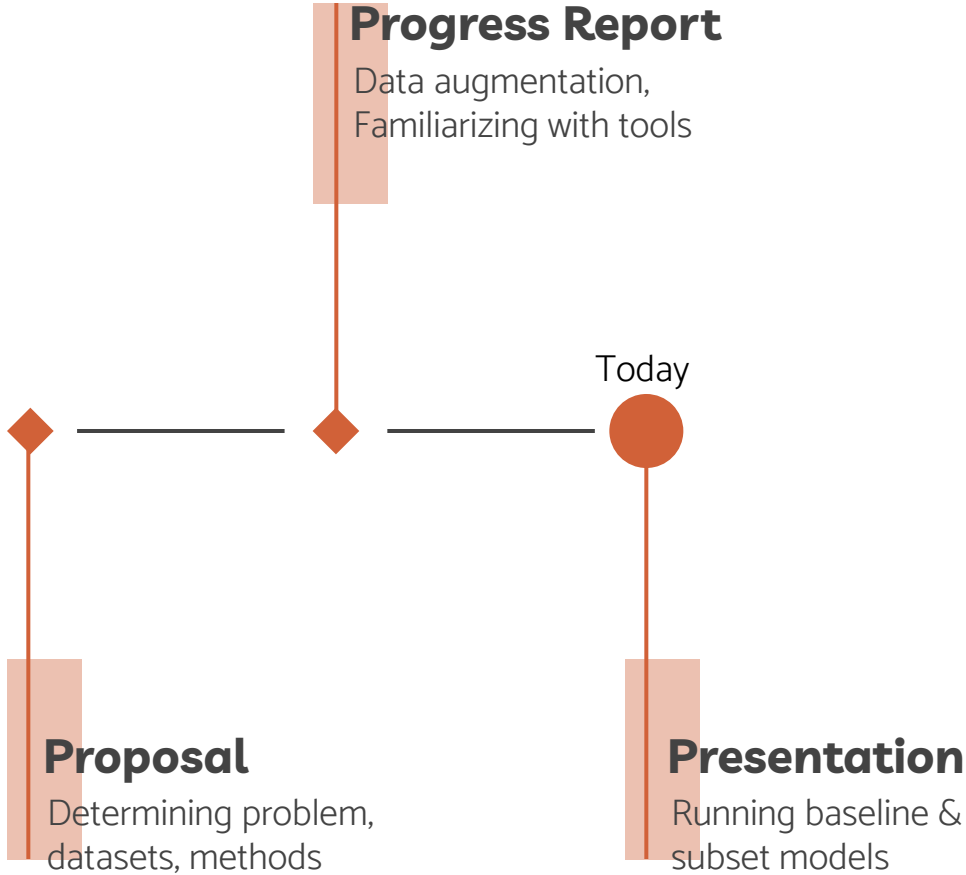
PLAN

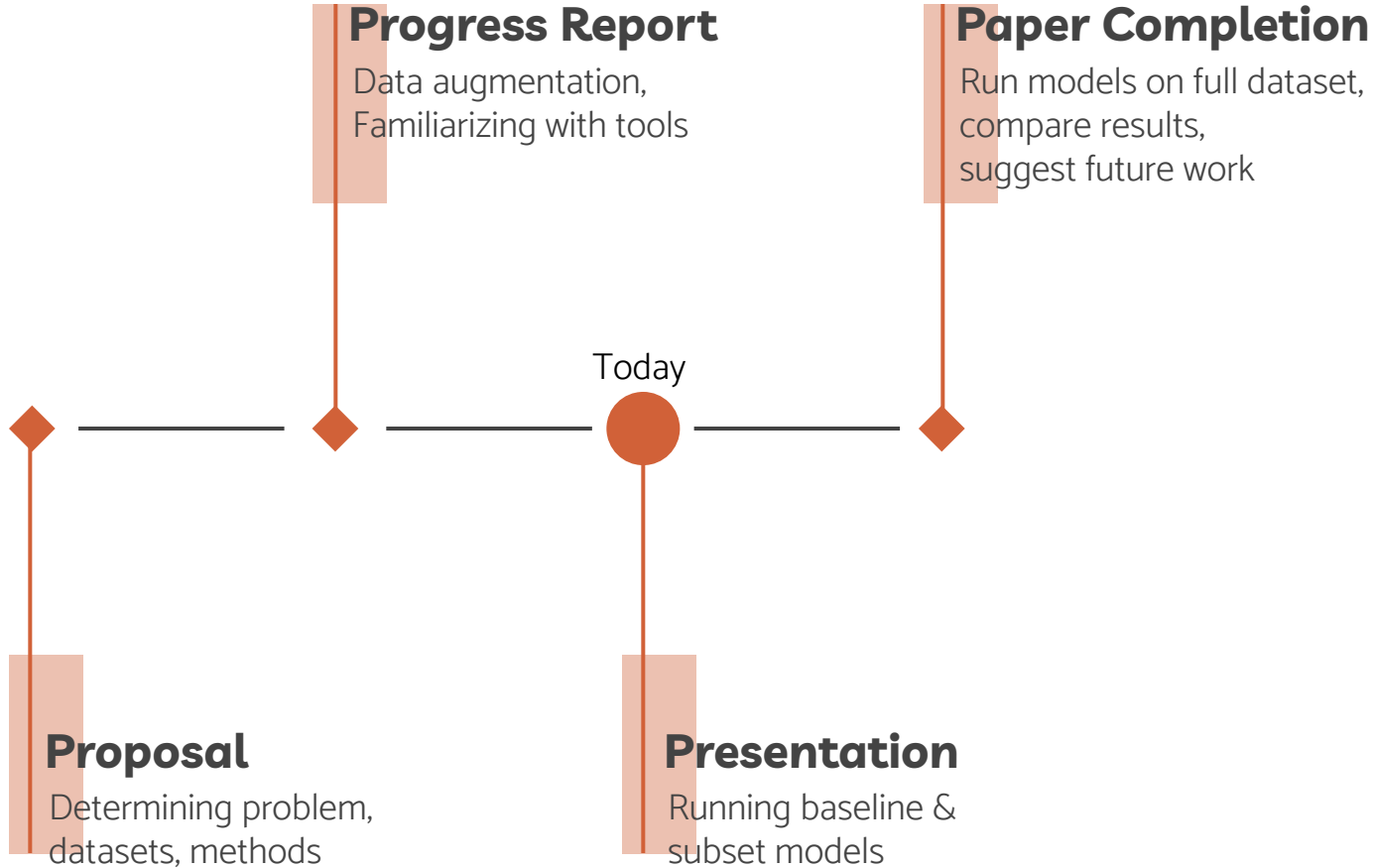


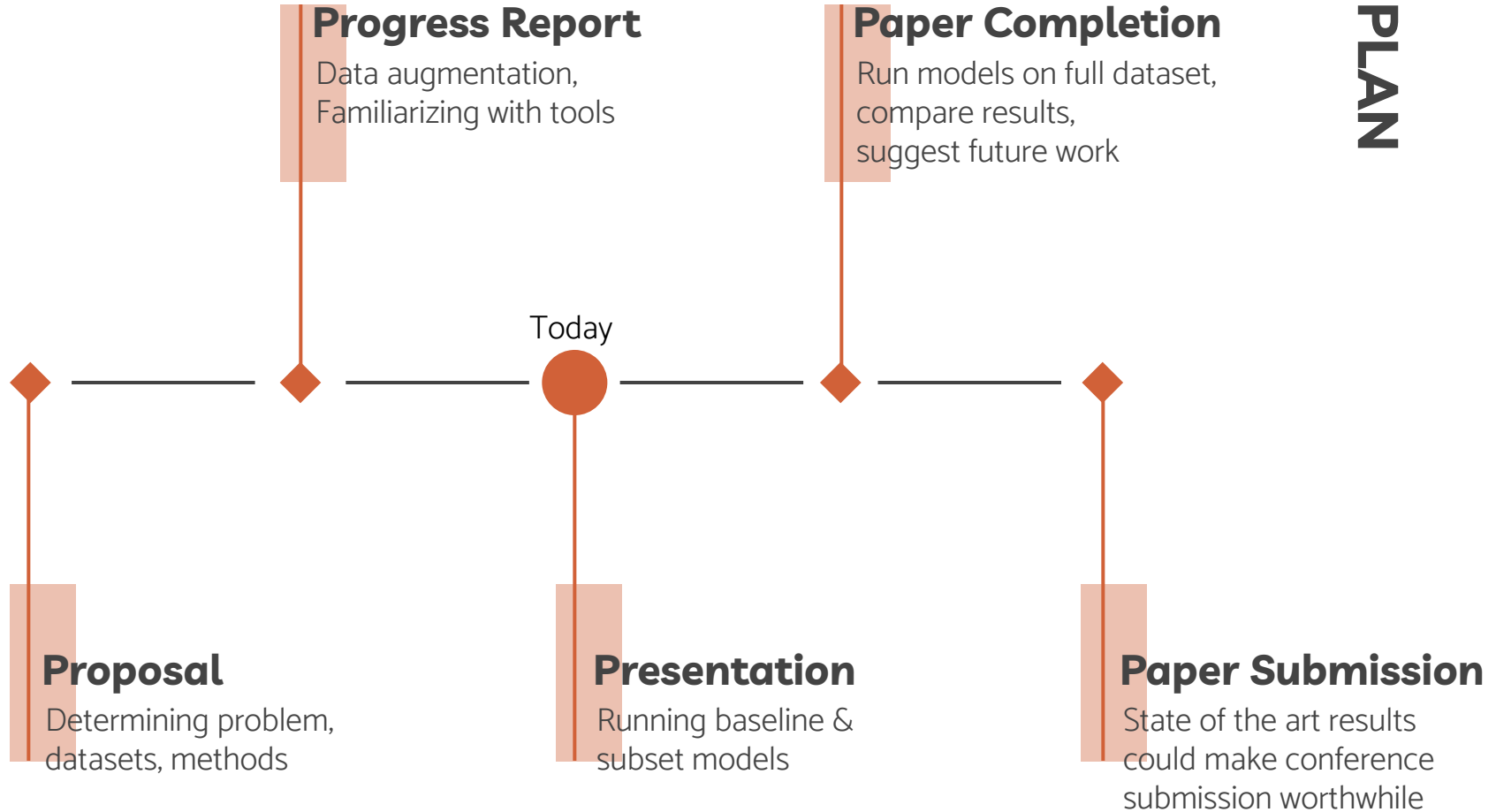
Proposal

Determining problem,
datasets, methods











Future work

- Run analyses on all 1.88M fires
- Experiment with new NN structures?
- Experiment with other adj. matrices?
- Reduction to binary classification
 - Arson is the most important case!

- https://commons.wikimedia.org/wiki/File:Deerfire_high_res_edit.jpg
- https://static01.nyt.com/images/2019/06/11/us/Oowaspnest-01/merlin_156060048_755263d2-7783-4275-ae26-583f7f568253-superJumbo.jpg
- https://www.nationalgeographic.com/content/dam/science/2019/10/09/california-wildfire/calif-wildfire-ap_18250148901527.adapt.1900.1.jpg
- <https://spektral.graphneural.network/>
- Presentation template by Slidesgo
- Icons by Flaticon
- Infographics by Freepik
- Images created by Freepik

THANK YOU

Does anyone have questions?



