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Behavior in Networks Studies Unit

Fundamentals and Applications of Weak Learners

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Introduction

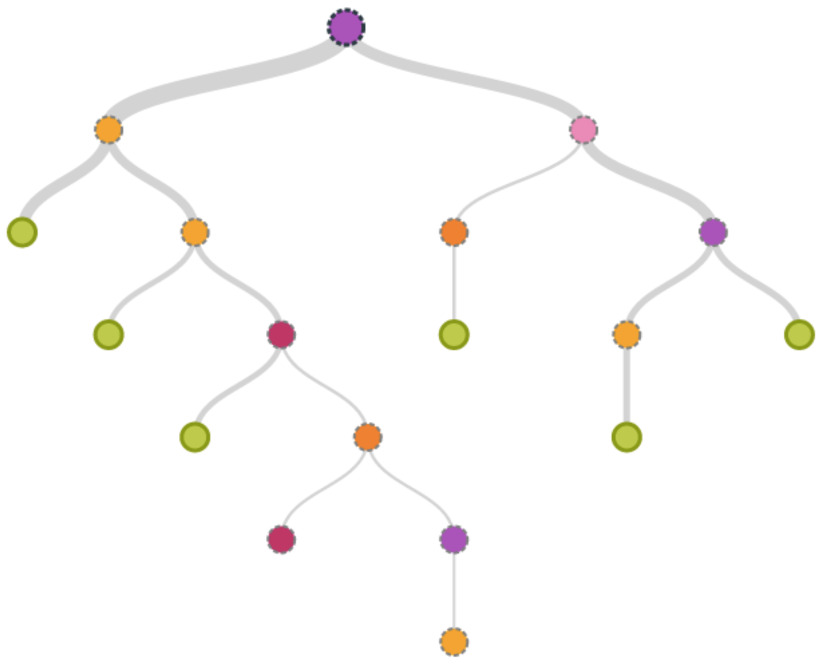
- When predicting, the least one can do is Random Guessing

- **Weak Learner**
- "A weak learner produces a classifier which is only slightly more accurate than random classification."

Pattern Classification Using Ensemble Methods, pg 21, 2010

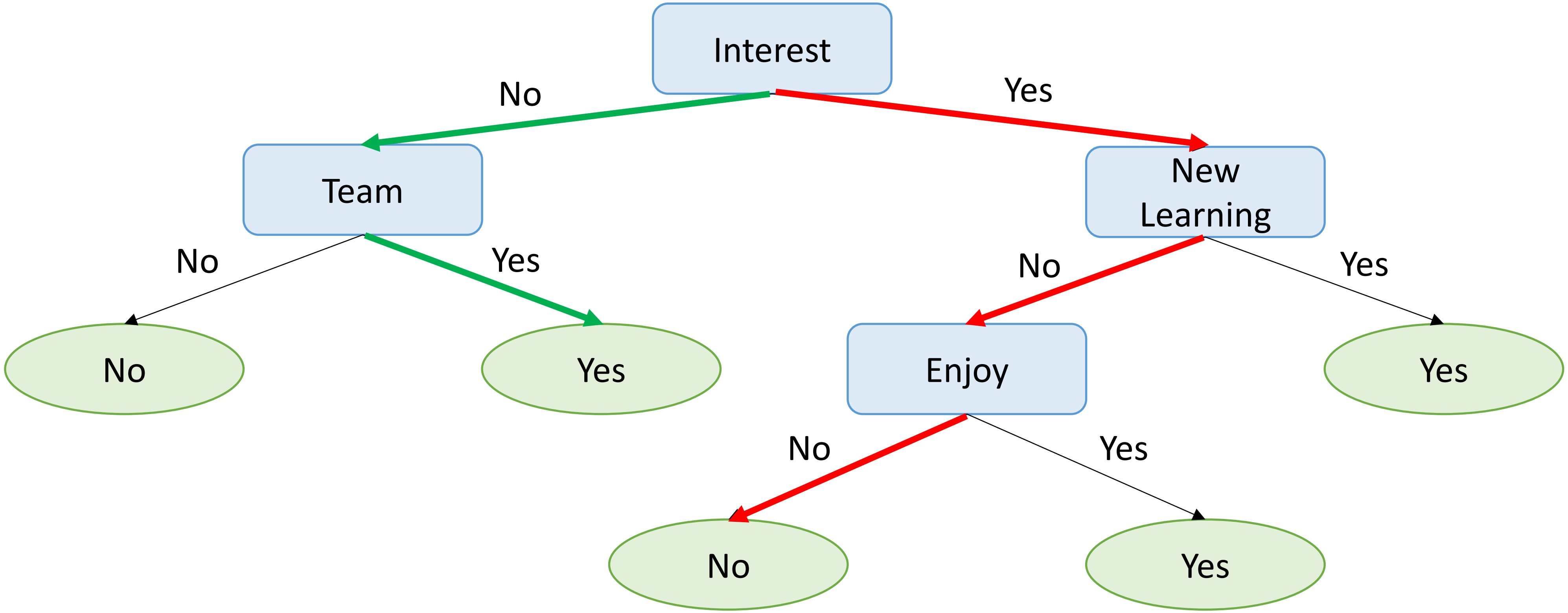
Introduction

- A popular example is Decision Tree.
- Weakness can be controlled by the depth of tree.
- Weakest tree: only one node and binary decision made on only one variable.



Introduction

- Example: Your decision to participate in the summer school.



Introduction

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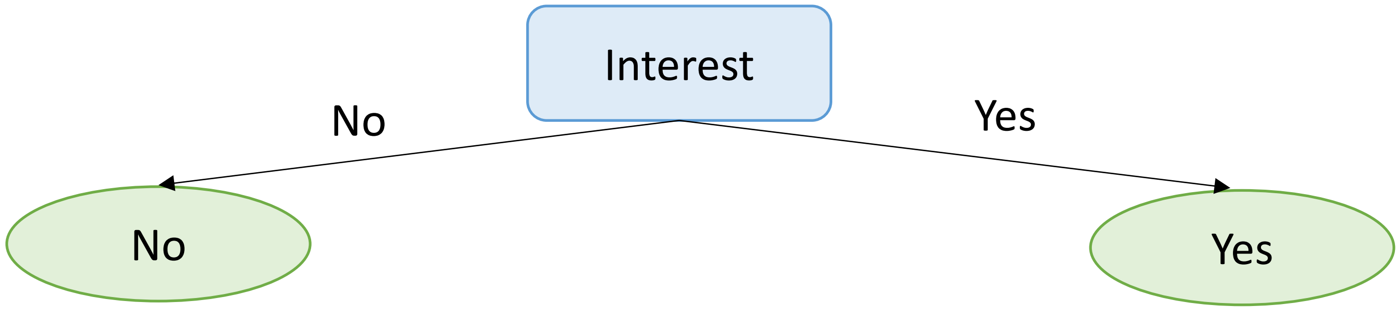


Introduction

- **Strong Learner**
- A strong learner produces a classifier that achieves arbitrarily good accuracy, better than random guessing.

- For modeling tasks, we aim to develop a strong classifier that makes predictions with good accuracy with high confidence.
- For instance, applying Support Vector Machines directly to the dataset.

Introduction

- In short

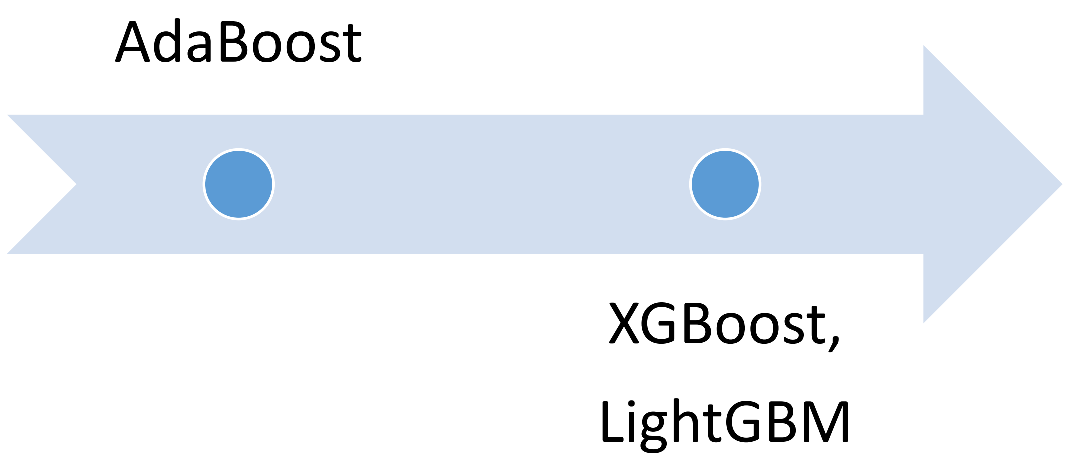
- Weak learners: Slightly better than random.
- Strong learners: Having good or even near-optimal accuracy.

- Are they equivalent?

YES

Boosting

- A strong learner can be constructed from many weak learners.
- This became the basis for boosting methods



Boosting

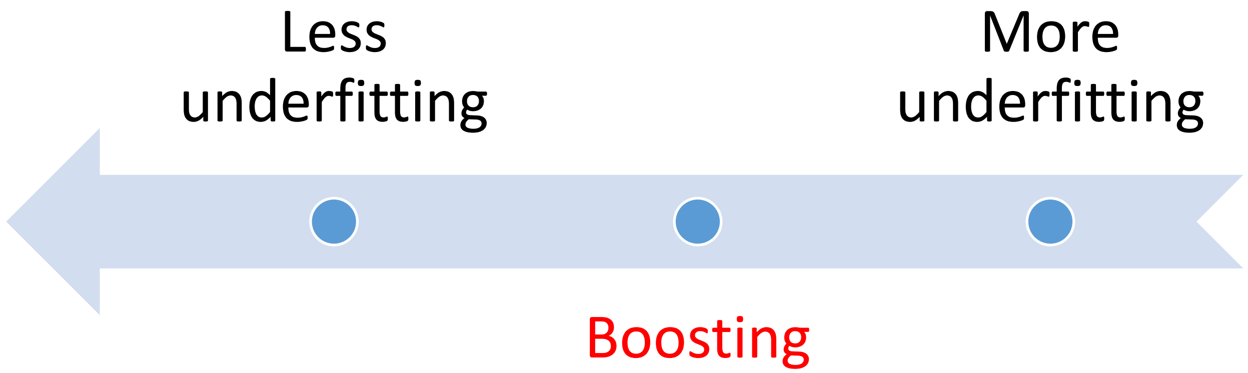
- Develop a large number of weak learners for a predictive learning problem.
- Combine them in a way to achieve a strong learner.

- Weak learners: Easy to prepare but not desirable.
- Strong learners: Hard to prepare and highly desirable.

Bagging vs. Boosting

Boosting

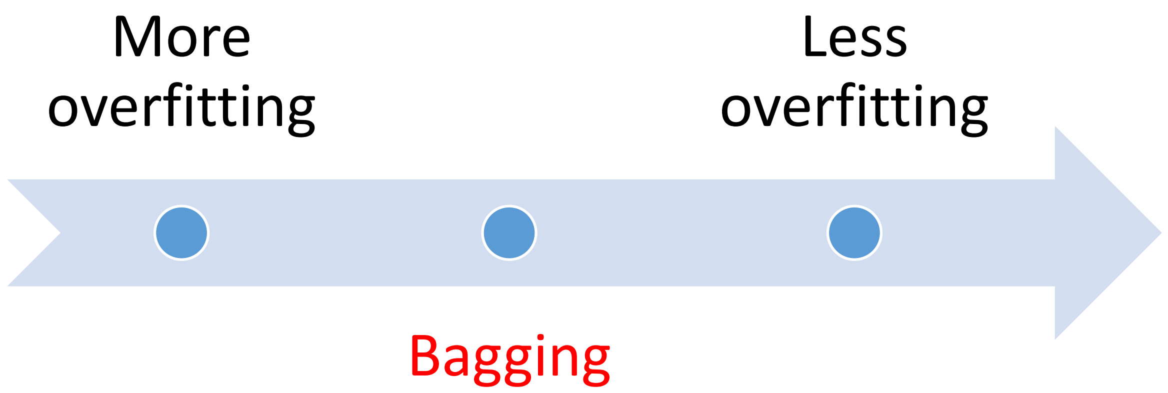
- Start with one decision tree stump (weak learner) and “focus” on the samples it got wrong.
- Train another decision tree stump that attempts to get these samples right.
- Repeat until a strong classifier is developed.



Bagging vs. Boosting

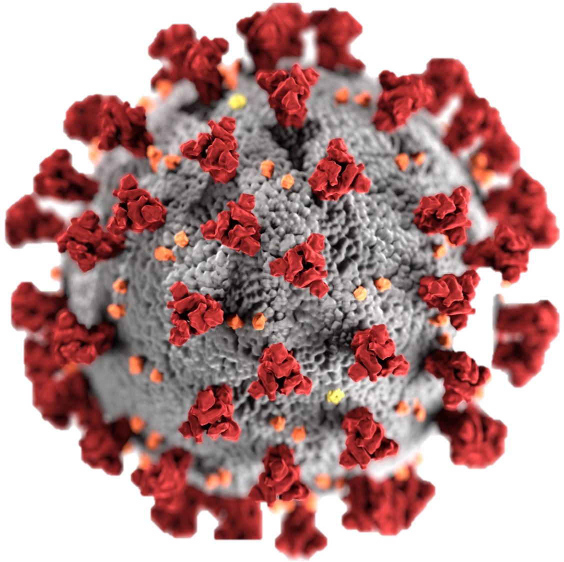
Bagging

- Train a number (ensemble) of decision trees from bootstrap samples of your training set.
- After the decision trees are trained, we can use them to classify new data via majority rule.



"Improving ridership by predicting train occupancy levels"

Consider a Scenario

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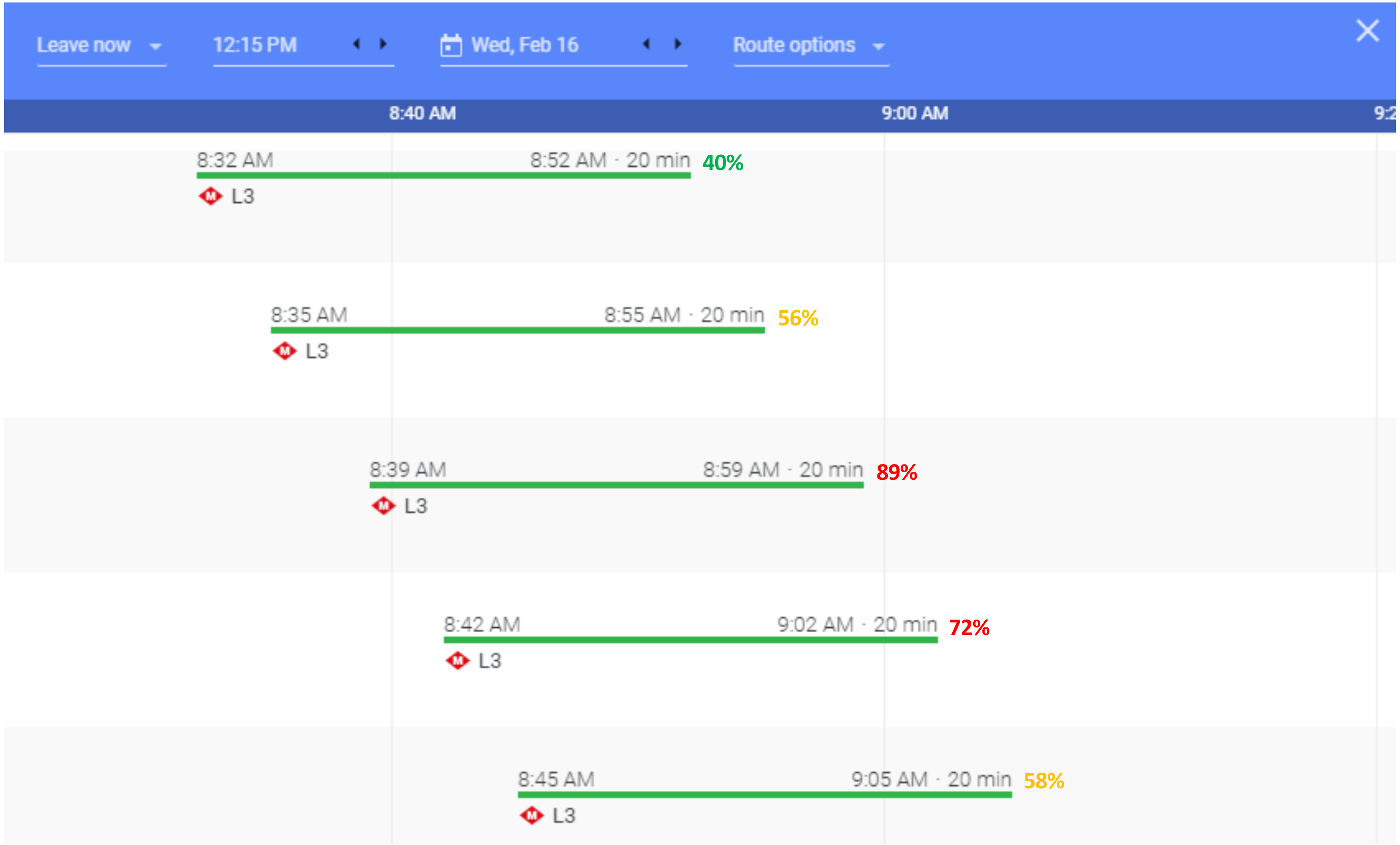
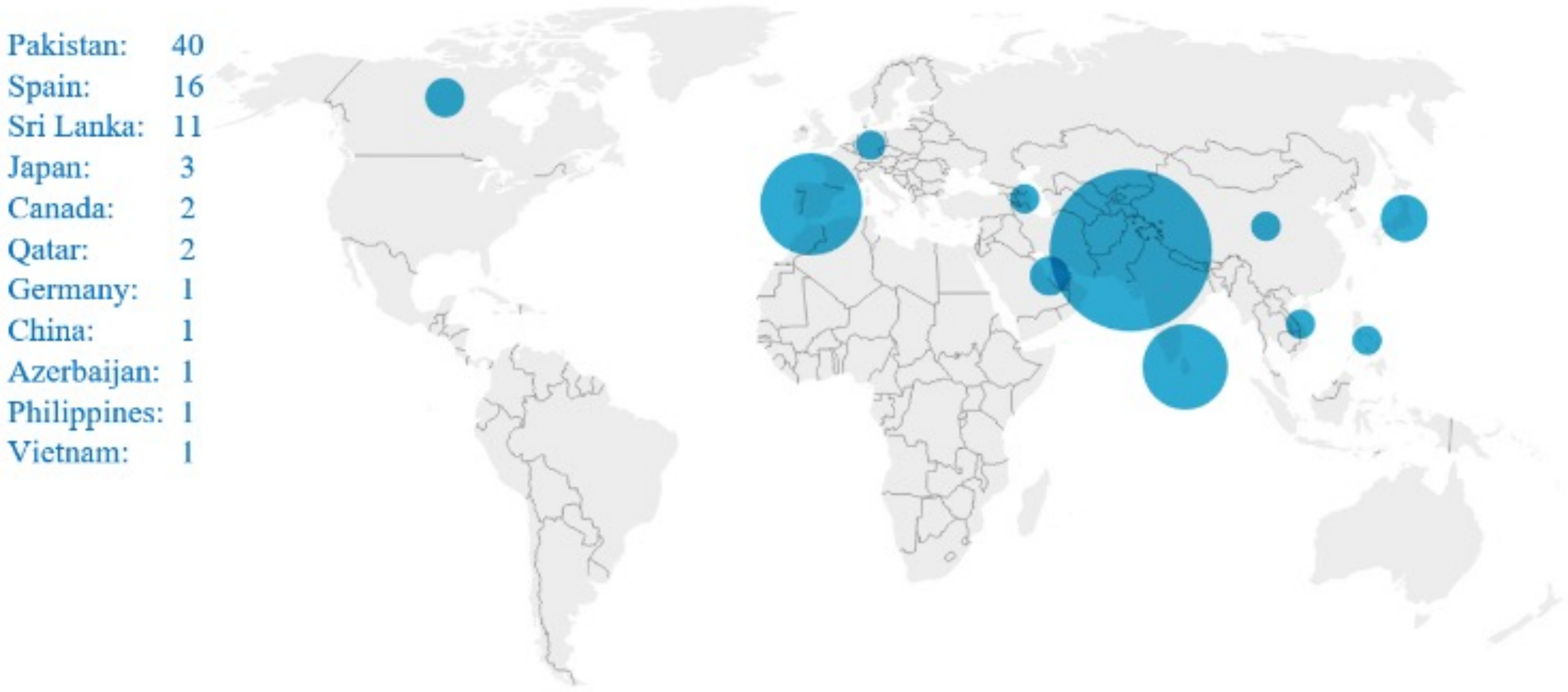


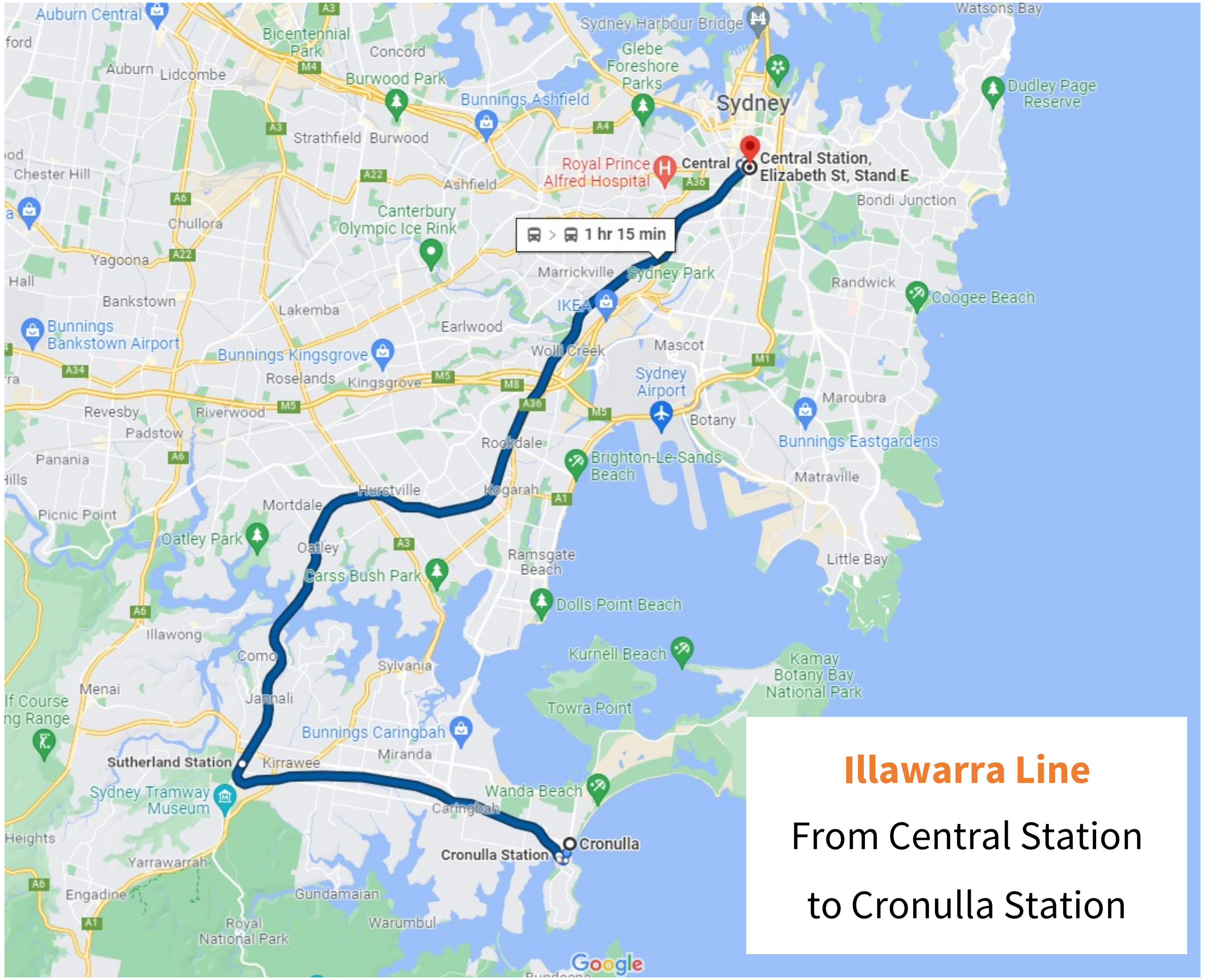
Leave now
12:15 PM
Wed, Feb 16
Route options
8:40 AM
9:00 AM
8:32 AM
8:52 AM · 20 min
40%
L3
8:35 AM
8:55 AM · 20 min
56%
L3
8:39 AM
8:59 AM · 20 min
89%
L3
8:42 AM
9:02 AM · 20 min
72%
L3
8:45 AM
9:05 AM · 20 min
58%
L3

Survey



- If future crowdedness levels are known 80% participants revealed that they will change their departure time and/or route to ensure less crowded transport.

Studied Train Route (NSW, Australia)

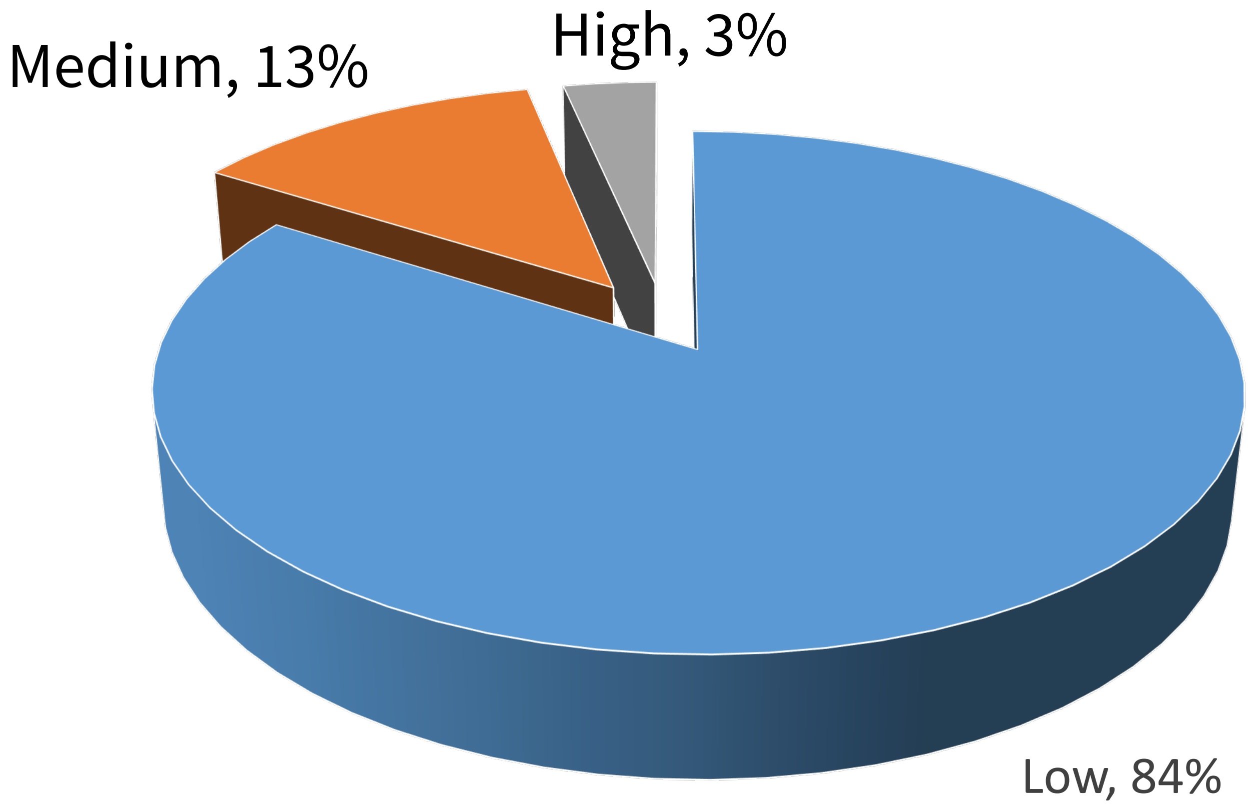


Illawarra Line

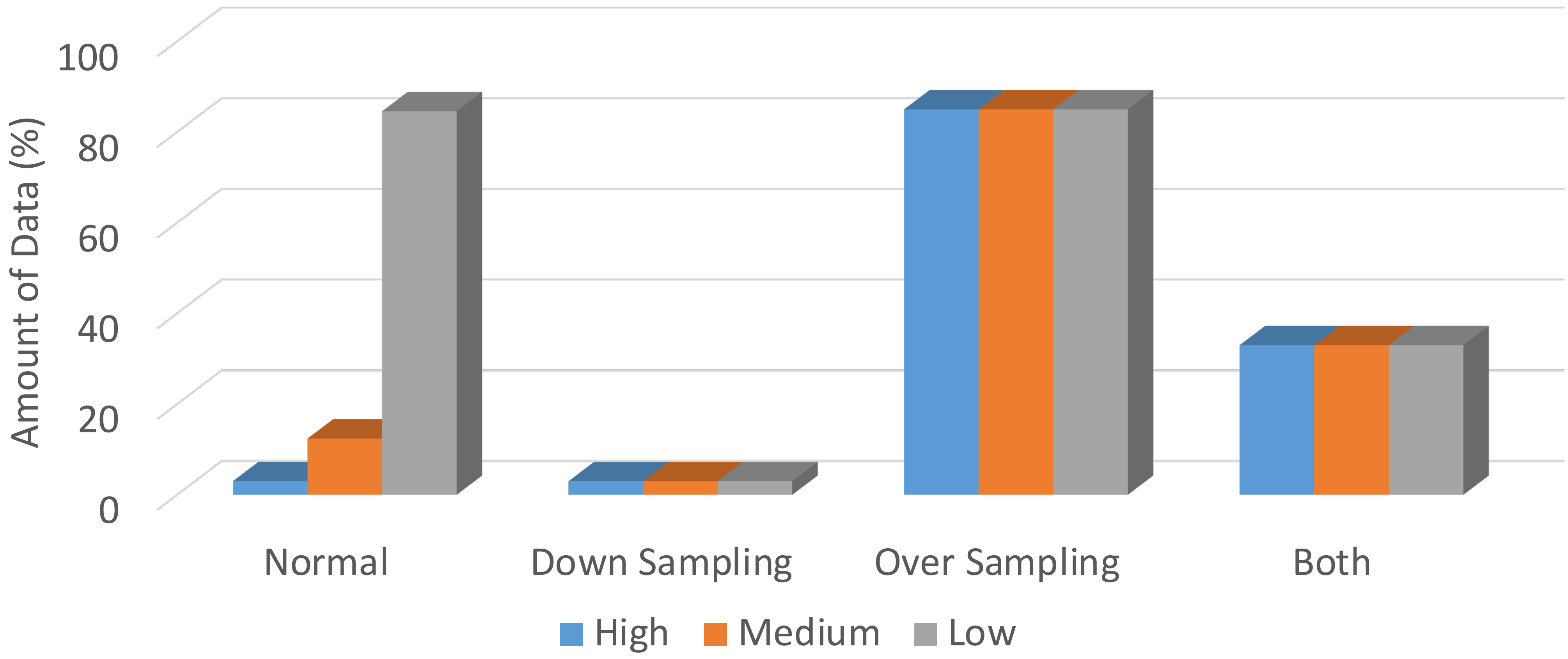
From Central Station

to Cronulla Station

Train Occupancy (Nov 2018 – Feb 2019)



Addressing Imbalanced Data



Overall Accuracy

Sampling	Classifier		
	XGB	RF	SVM
Normal	0.941	0.956	0.951
Down Sampling	0.930	0.940	0.935
Over Sampling	0.958	**0.959**	0.936
Both	0.955	0.955	0.939

Macro-averaged F1 Score

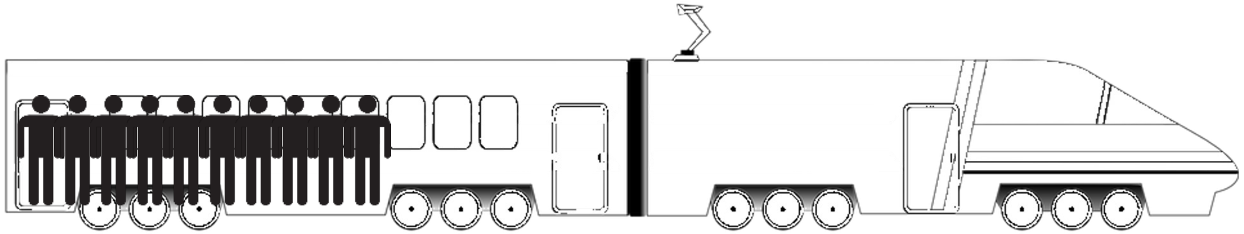
Sampling	Classifier		
	XGB	RF	SVM
Normal	0.824	0.876	0.865
Down Sampling	0.831	0.864	0.844
Over Sampling	**0.891**	0.883	0.826
Both	**0.891**	0.889	0.838

Challenges

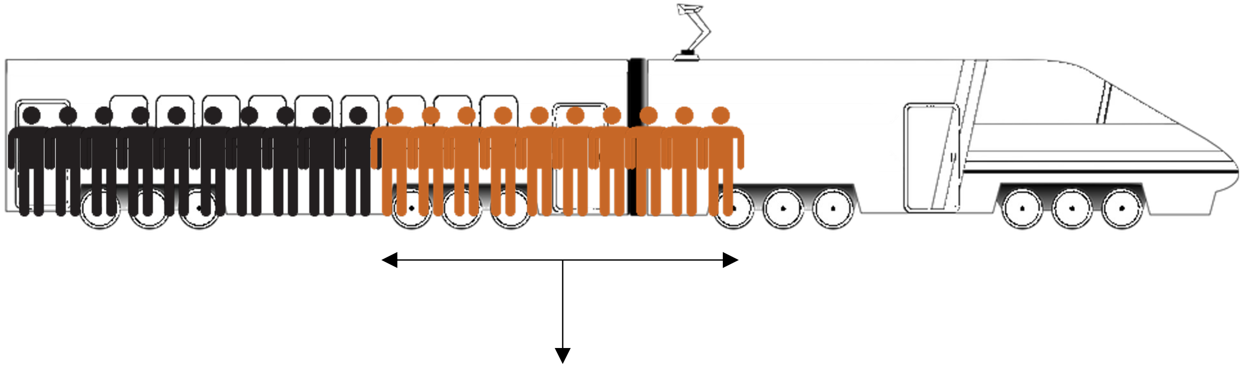
Imbalanced Data: Biased learning leading to skewed results.

Attracted Occupancy: Predicted Crowdedness values would be affected by changed travel behavior.

Predicted Crowdedness Level



Actual Crowdedness Level



Attracted Occupancy

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Annex

- $\text{Precision} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Positive}}$

- $\text{Recall} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Negative}}$

- $\text{Accuracy} = \frac{\text{True Positive} + \text{True Negative}}{\text{True Positive} + \text{True Negative} + \text{False Positive} + \text{False Negative}}$

- $\text{F1 Score per class}, \text{F1}_c = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$

- $\text{Macro} - \text{Averaged F1 Score} = \frac{\text{F1}_{\text{High}} + \text{F1}_{\text{Medium}} + \text{F1}_{\text{Low}}}{3}$