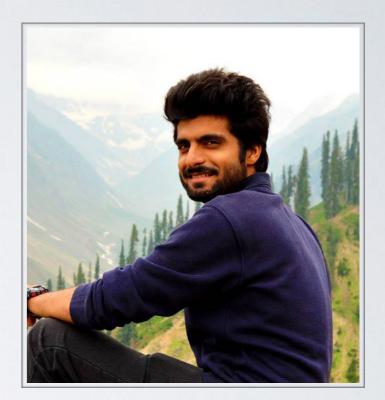
PREDICTING END-TO-END CAPACITY OF PLC-WIFI PATHS

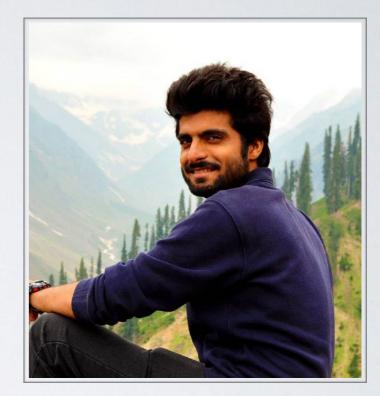
Khurram Javed Supervisors : Victor Kristof and Sébastien Henri

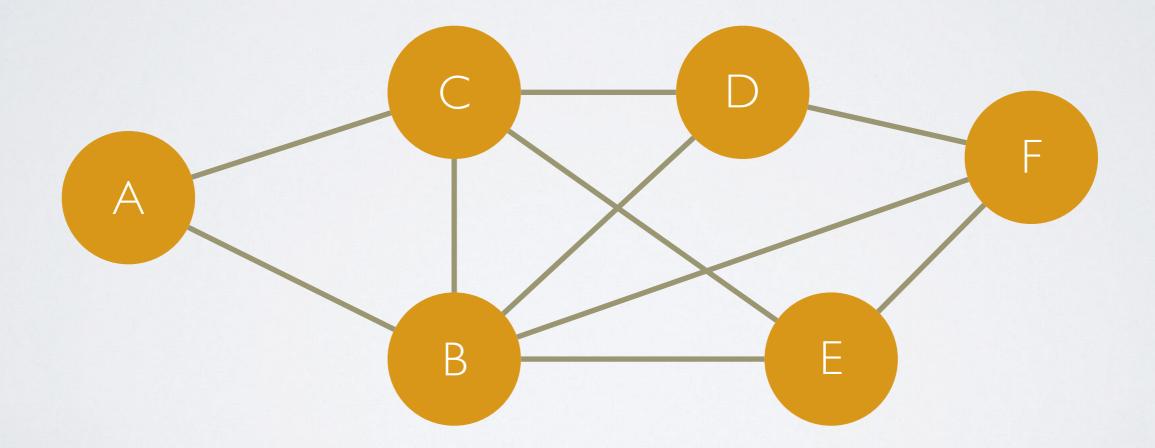
INTRODUCTION



INTRODUCTION

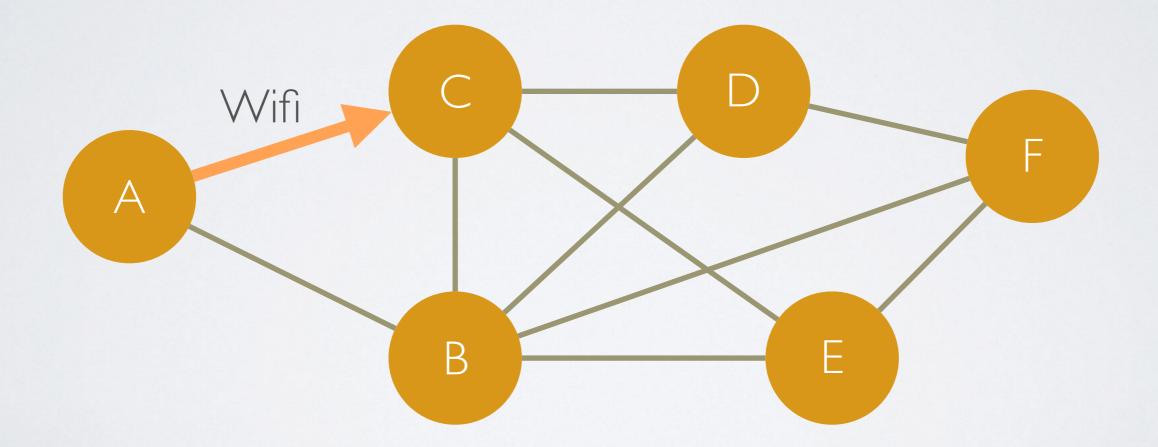
- 4th Year Student of BS Comp Sci, NUST.
- From Islamabad, Pakistan
- Hopes and dreams of becoming a researcher in CS/AI.
- Working at LCA3 for 3 months.





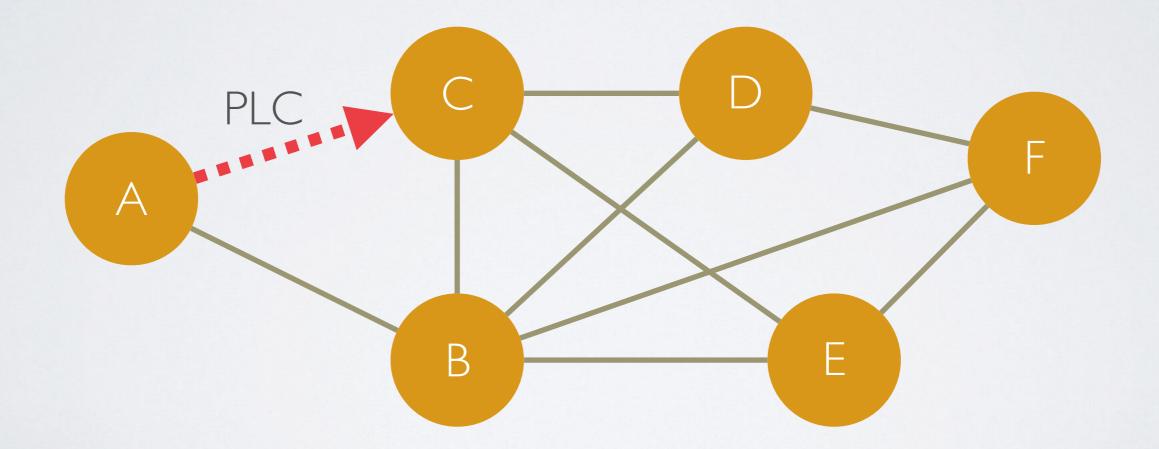
Ad-Hoc Network

2/20

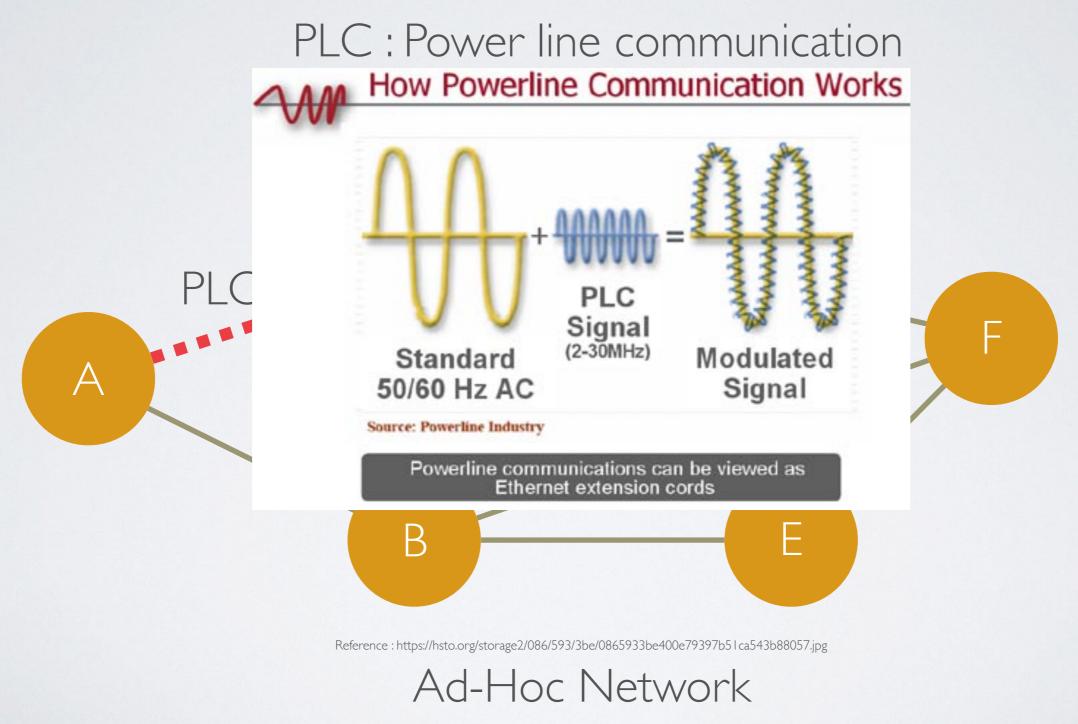


Ad-Hoc Network

2/20

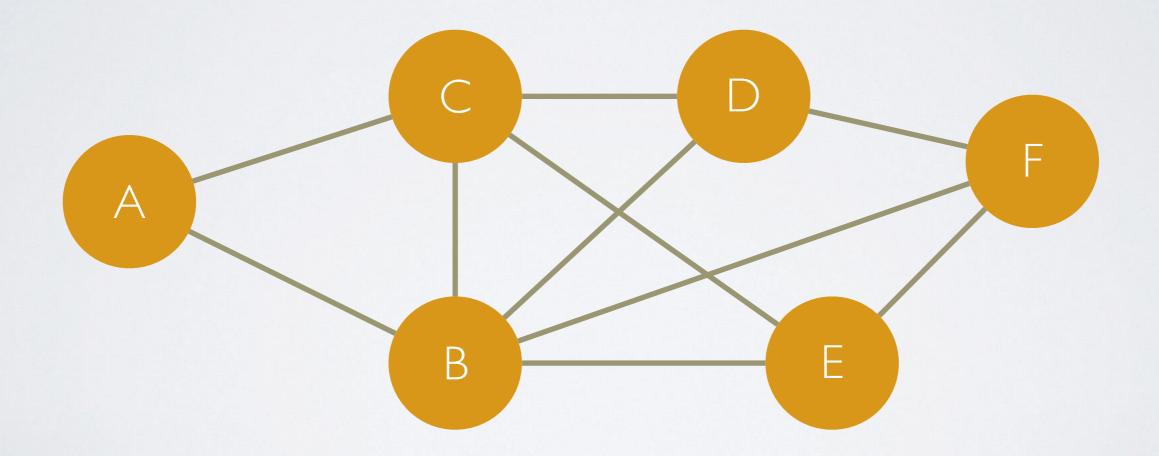


Ad-Hoc Network



^{2/20}

GOAL: Transmit data from A to F

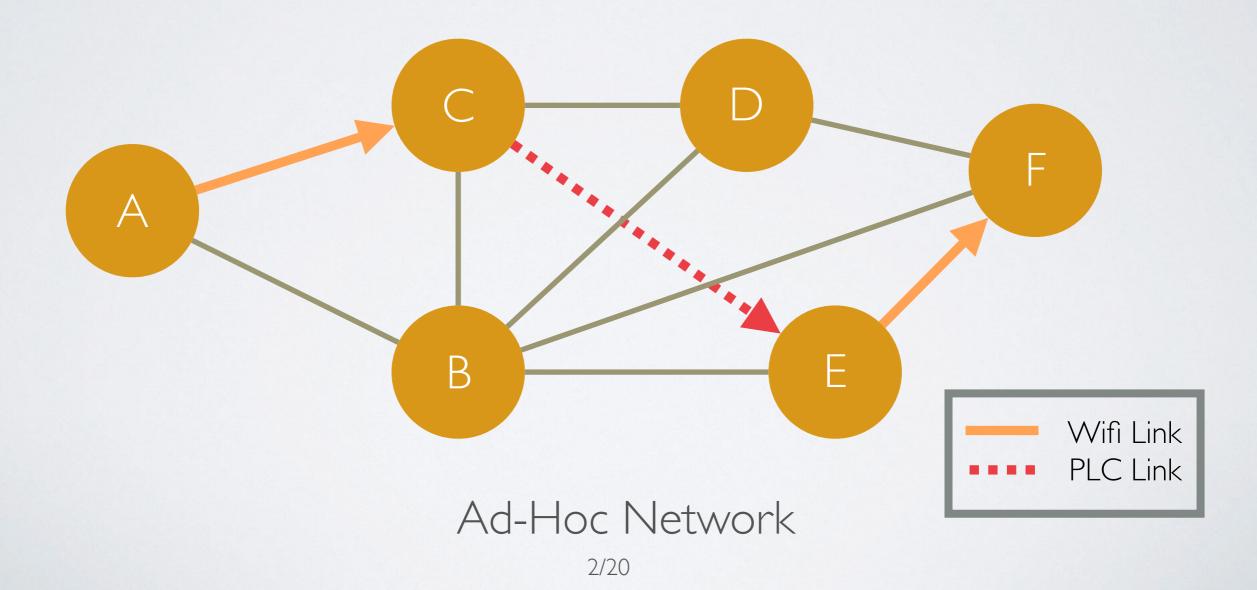


Ad-Hoc Network

2/20

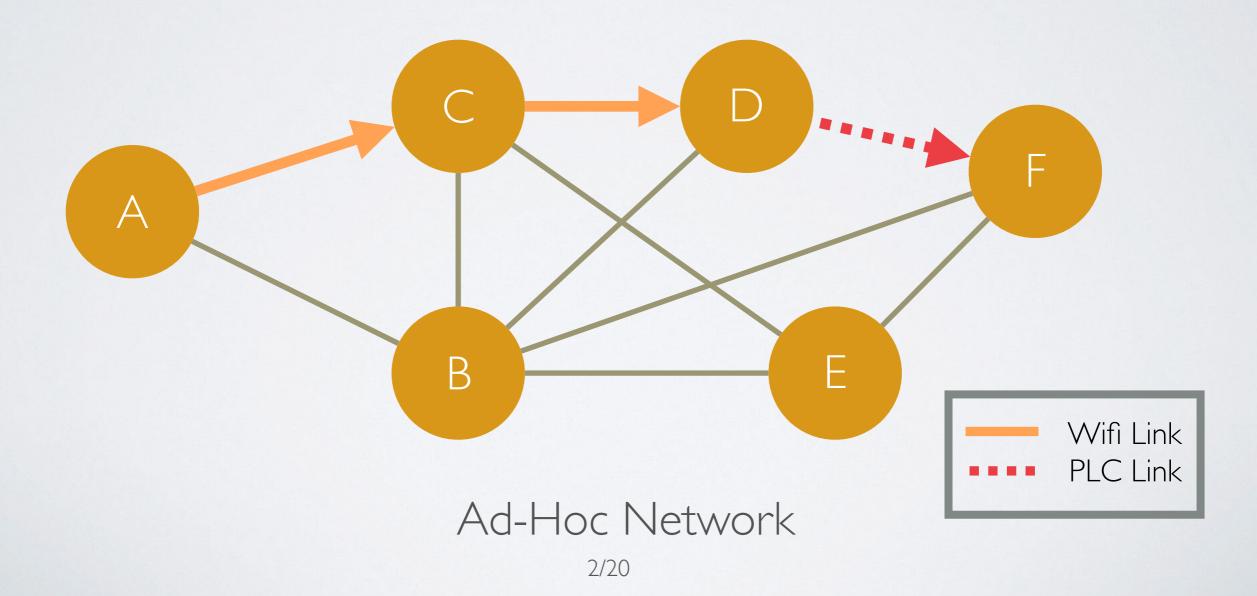
GOAL: Transmit data from A to F

Possibility I : A_wC_pE_wF



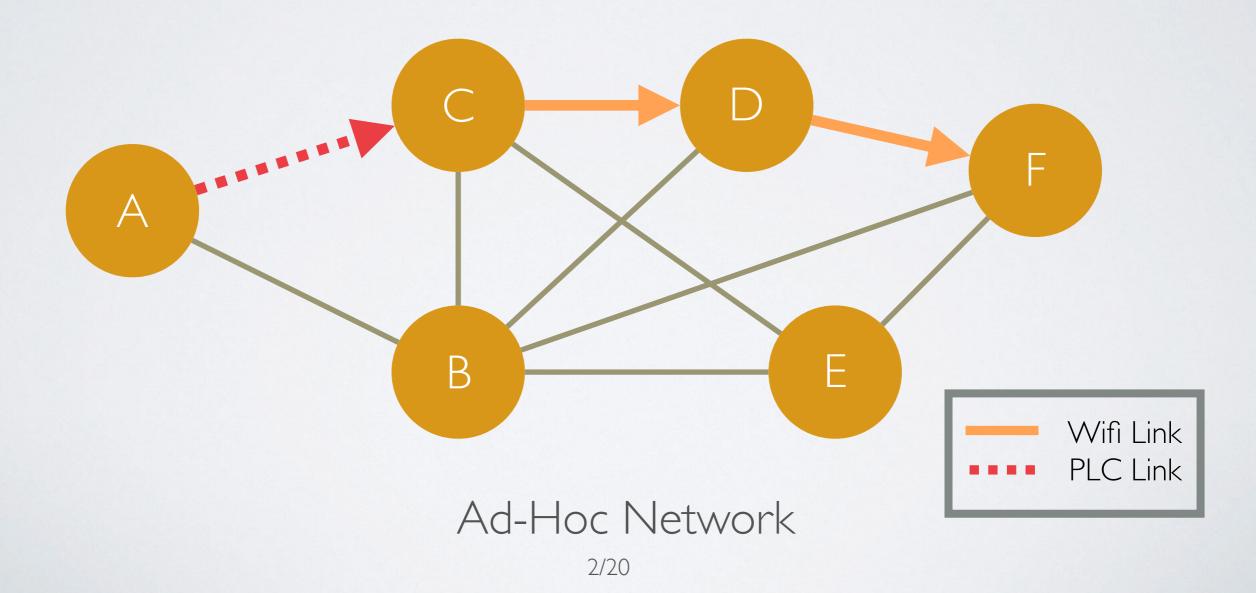
GOAL: Transmit data from A to F

Possibility 2 : A_wC_wD_pF



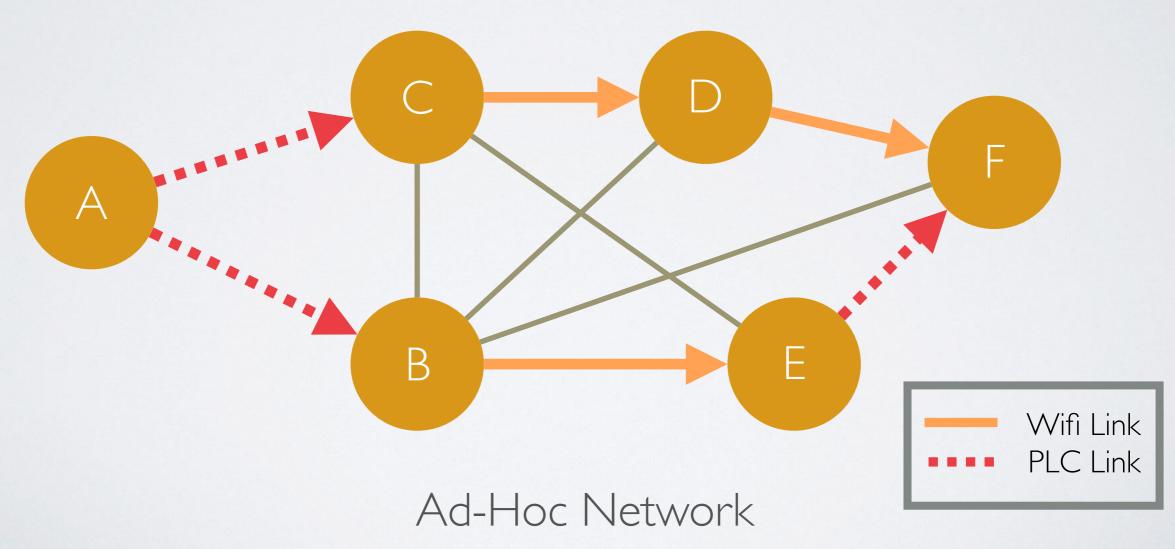
GOAL: Transmit data from A to F

Possibility 3: ApCwDwF



GOAL: Transmit data from A to F

Possibility 4: $A_pC_wD_wF$ and $A_pB_wE_pF$



2/20

Multiple options!

Multiple options!

How do we decide which one is the best?

Multiple options!

How do we decide which one is the best? Answer : Pick to maximize capacity!

PROBLEM STATEMENT

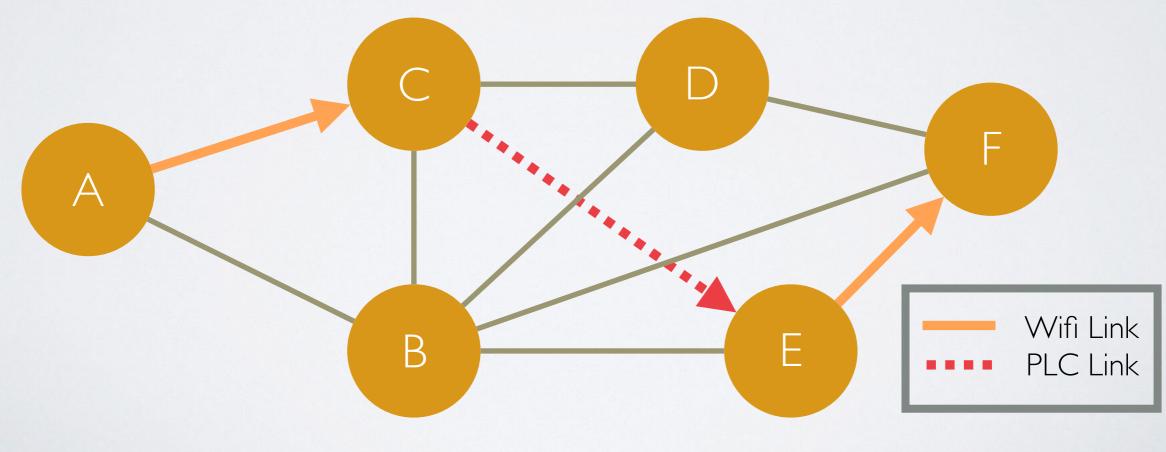
PROBLEM STATEMENT

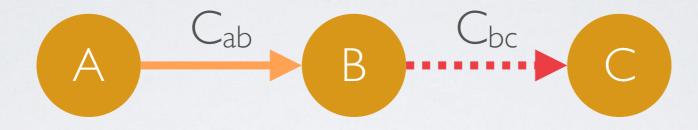
"'Predict end-to-end capacity of PLC-Wifi paths."

PROBLEM STATEMENT

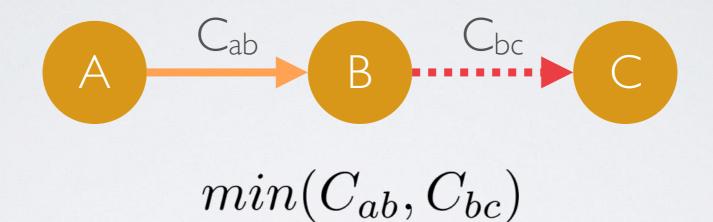
"'Predict end-to-end capacity of PLC-Wifi paths."

What is the capacity of $A_w C_p E_w F$?

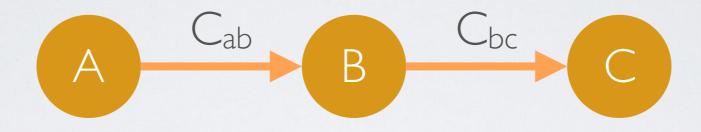












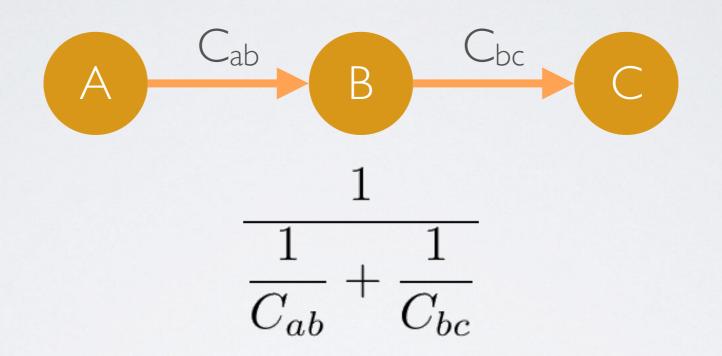


Not as straightforward!



Not as straightforward! Reason : Interference

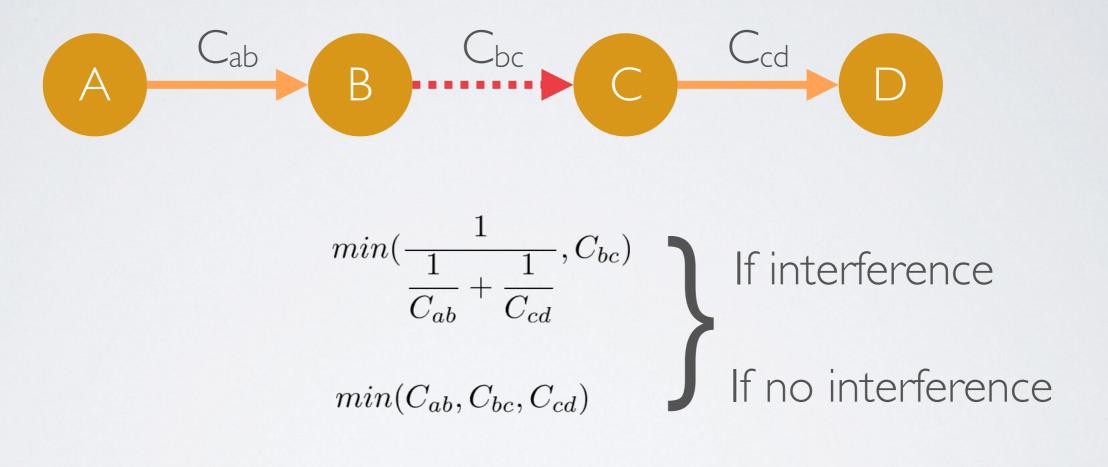




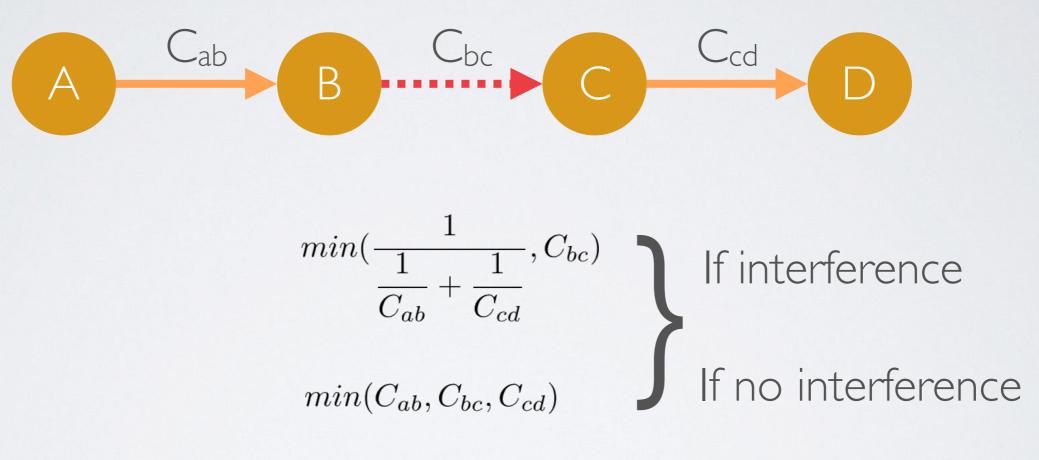




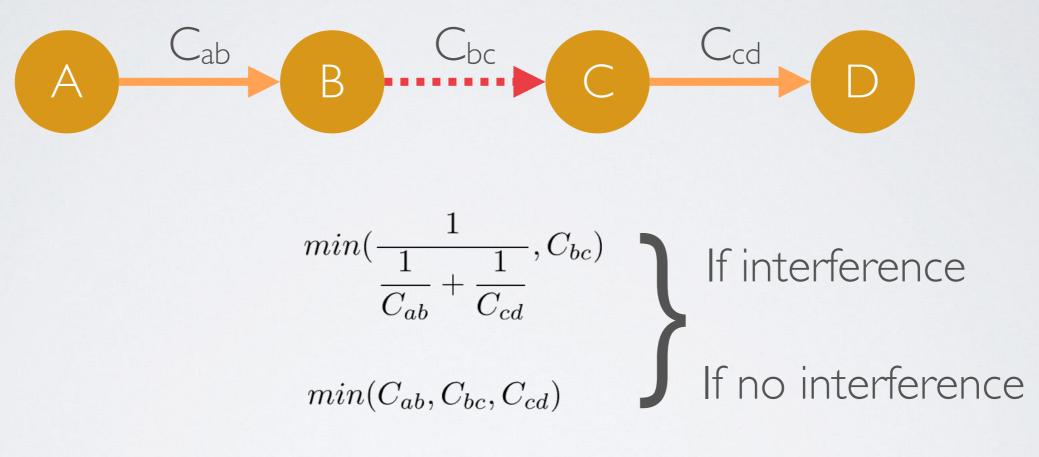




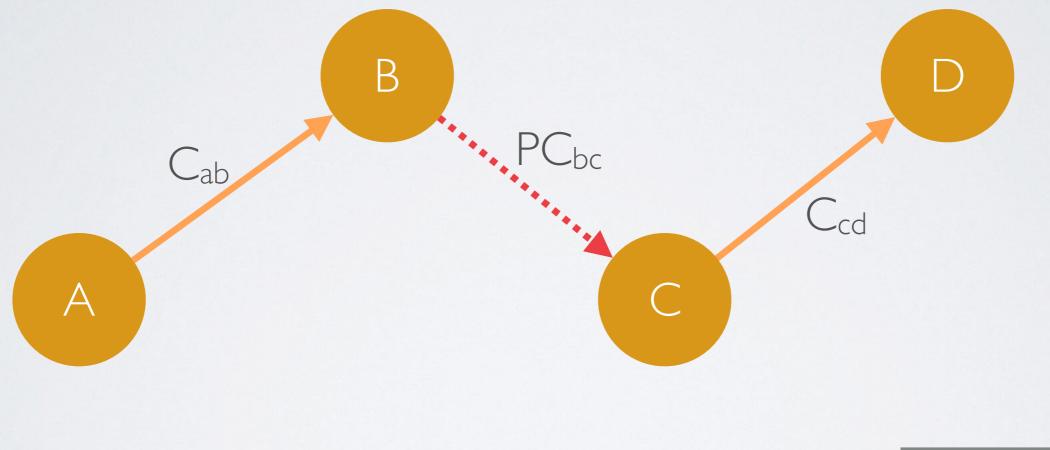




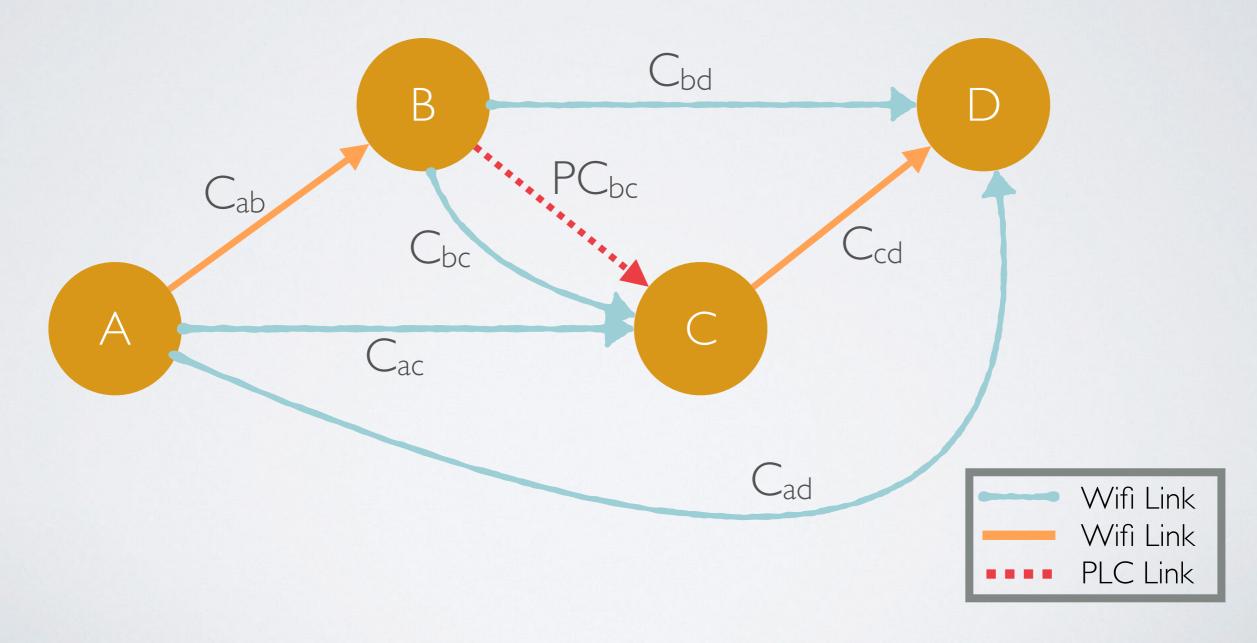
Assumes interference is binary! Assumes C can always tell when A is transmitting (And vice-versa) !

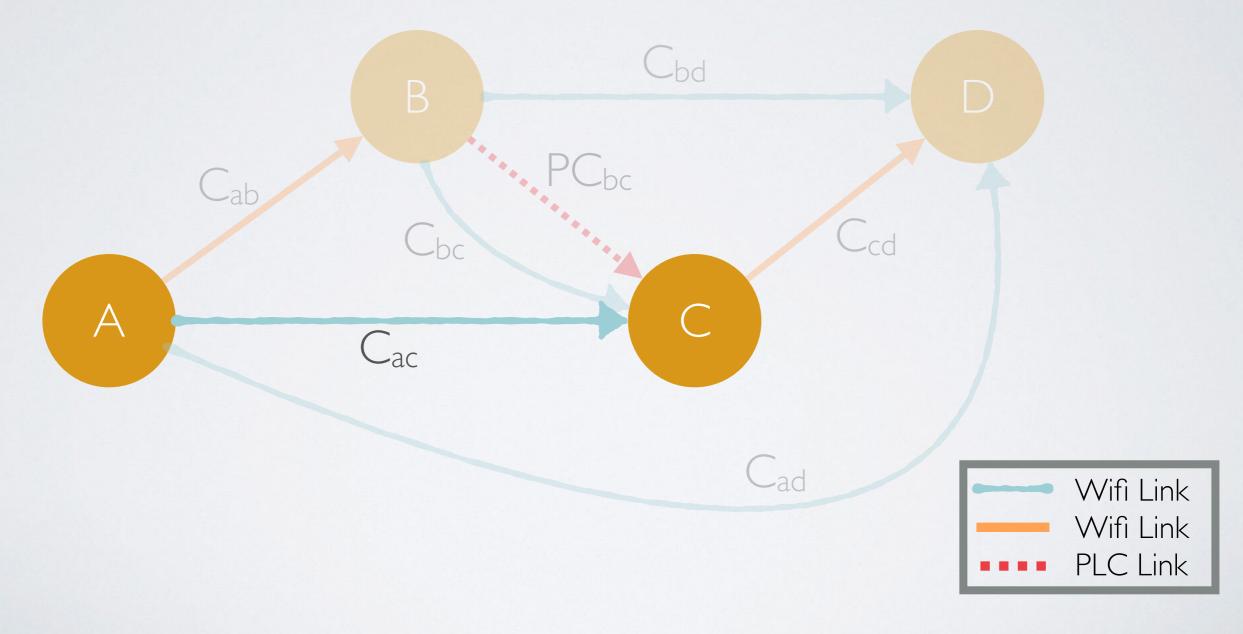


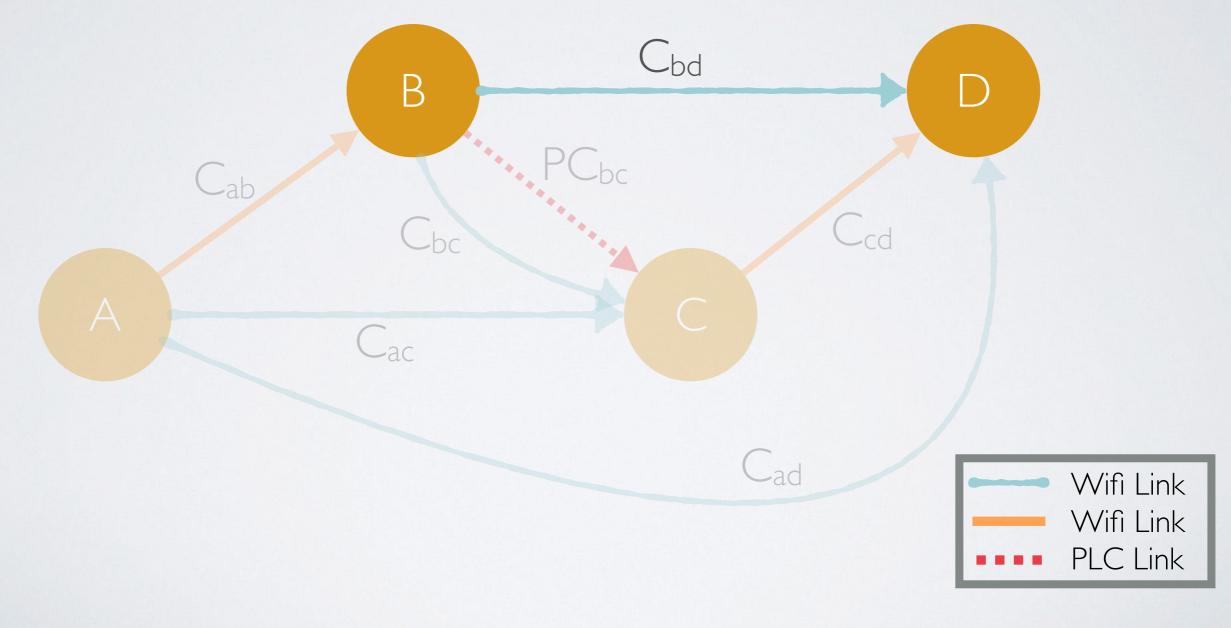
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MODEL AND DATA

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 $Y = W_1^T . X_{LC}$

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 $Y = W_1^T \cdot X_{LC} + W_2^T \cdot X_{BP}$

MODEL AND DATA

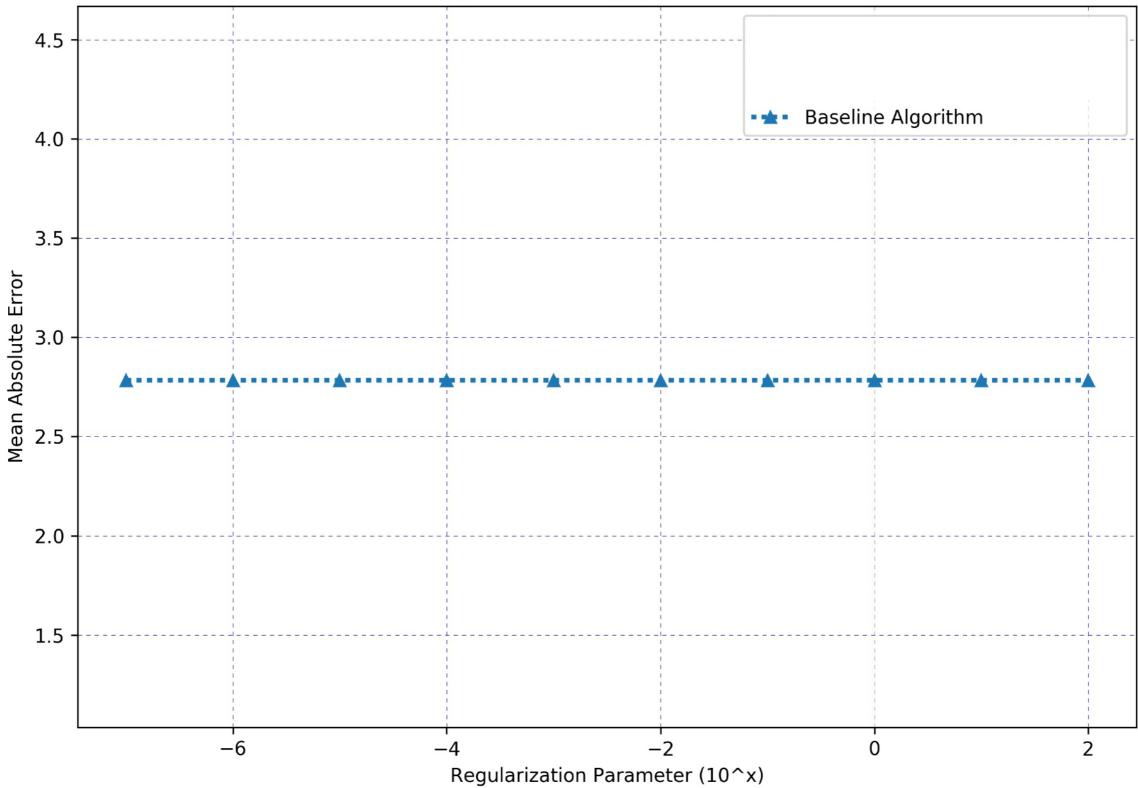
$Y = W_1^T . X_{LC} + W_2^T . X_{BP} + W_3^T . P^2 (X_{LC} \times X_{BP})$

MODEL AND DATA

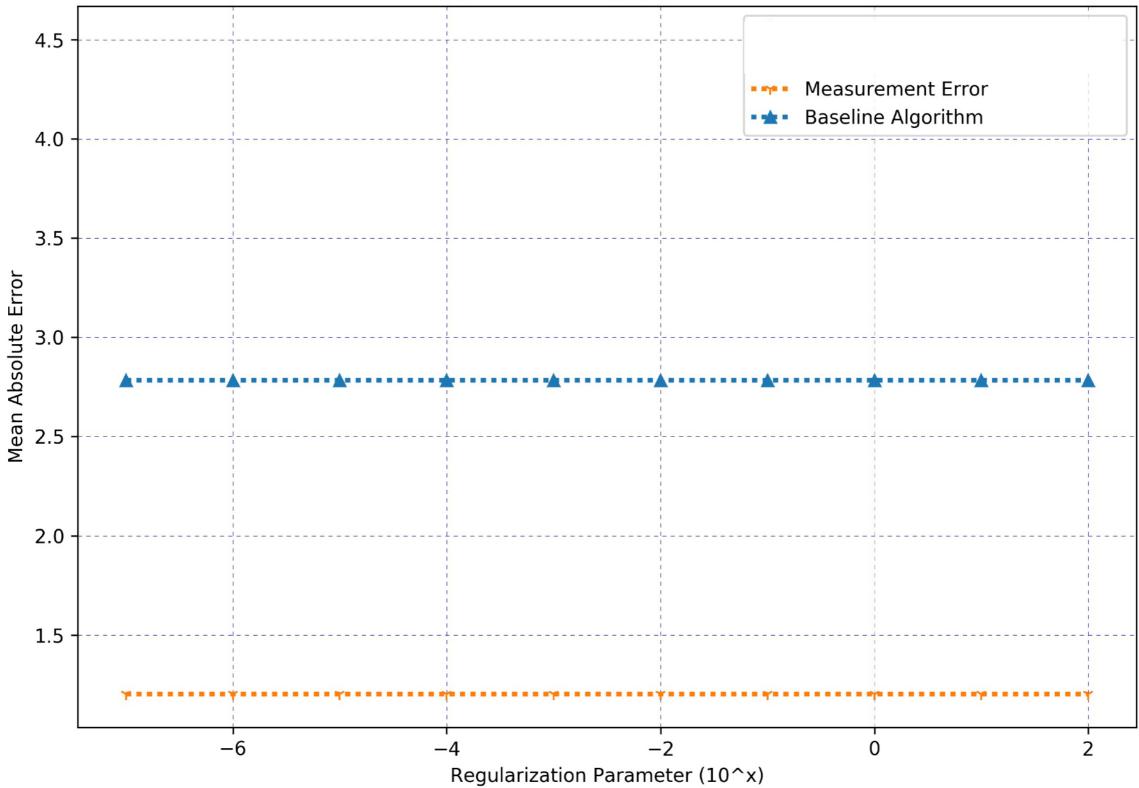
$Y = W_1^T . X_{LC} + W_2^T . X_{BP} + W_3^T . P^2 (X_{LC} \times X_{BP})$

Collected on a 22 node testbed using UDP traffic.

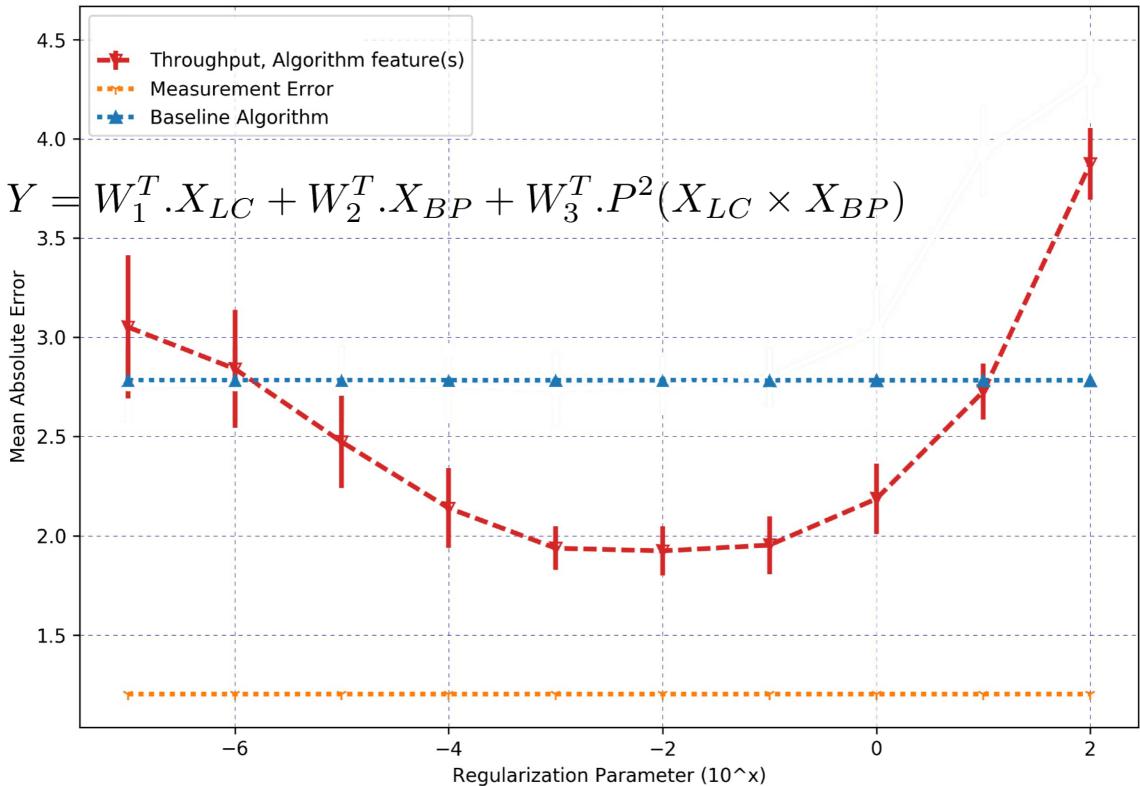
Impact of Throughput Features



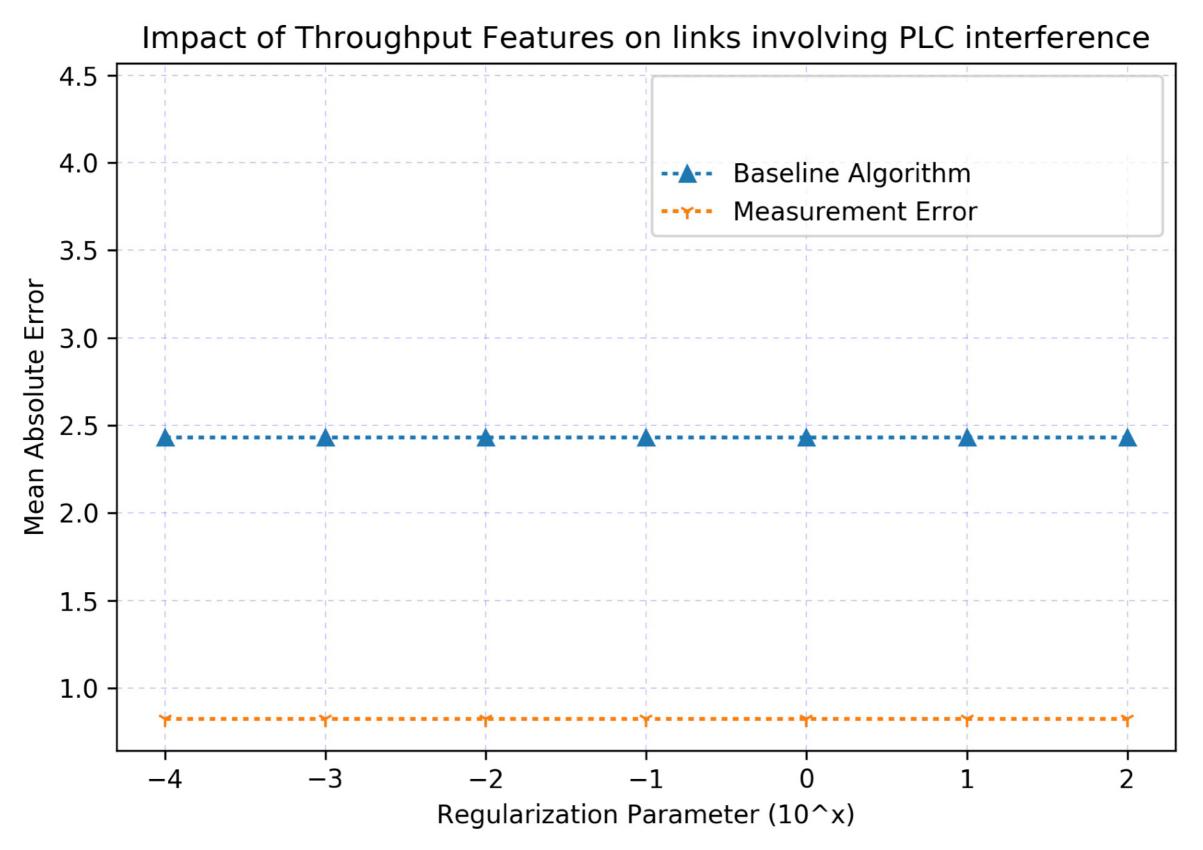
Impact of Throughput Features



Impact of Throughput Features

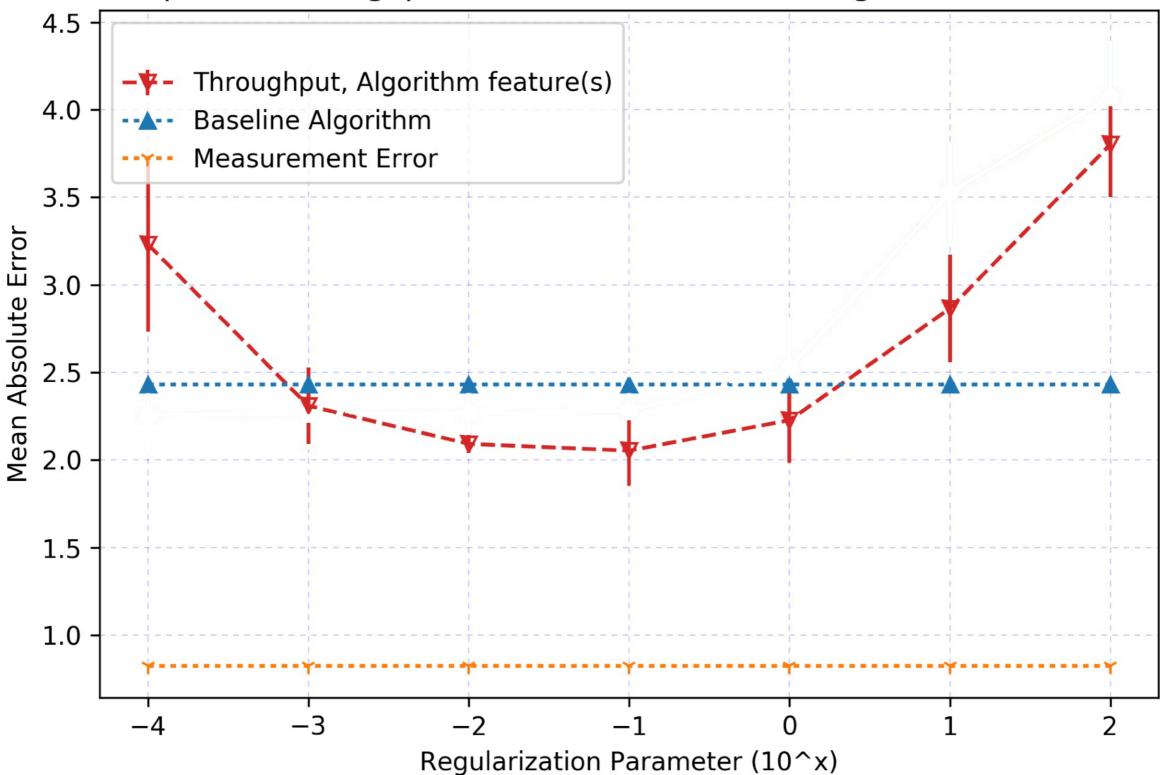


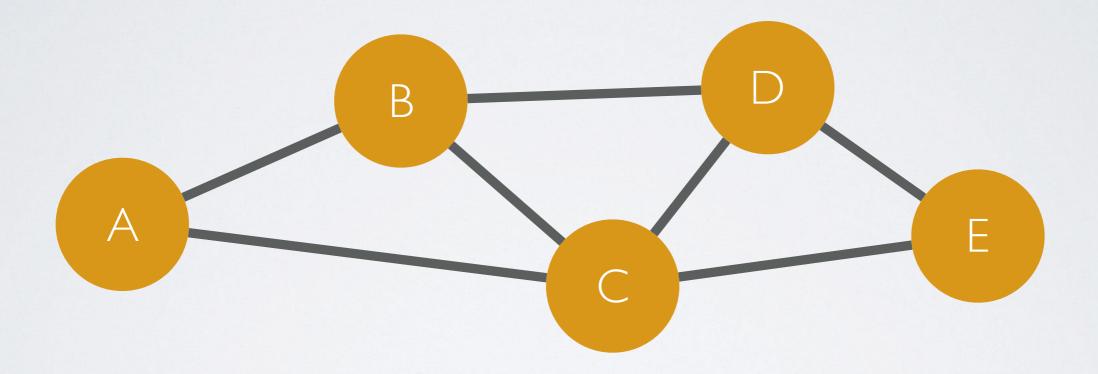
PWP Paths

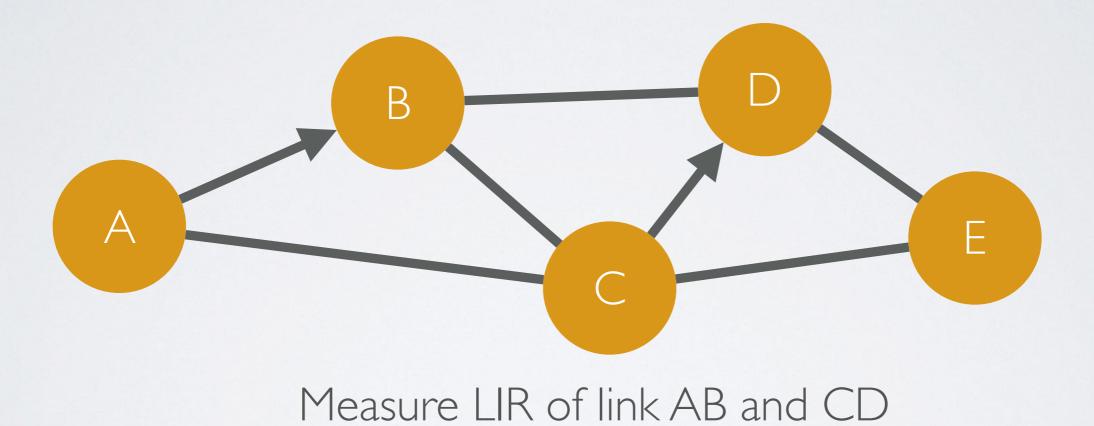


PWP Paths

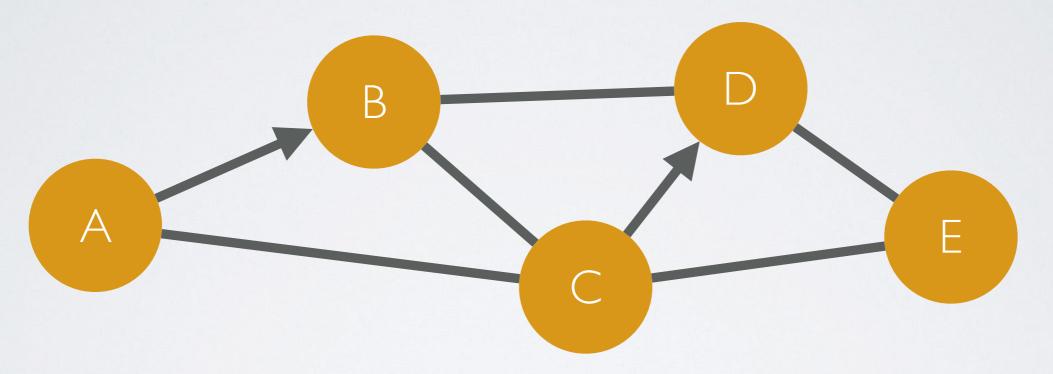
Impact of Throughput Features on links involving PLC interference



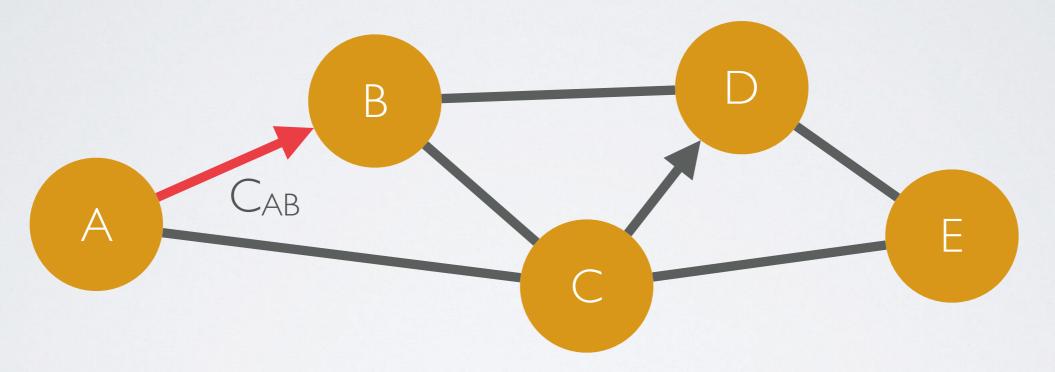




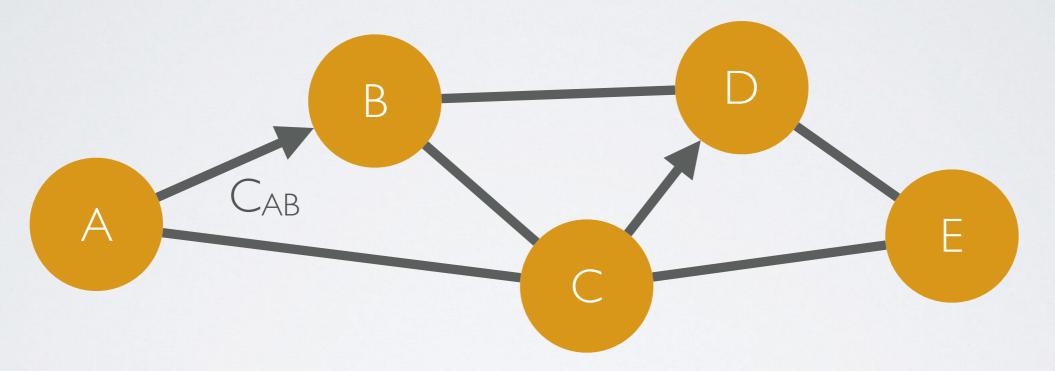
• Metric to measure interference



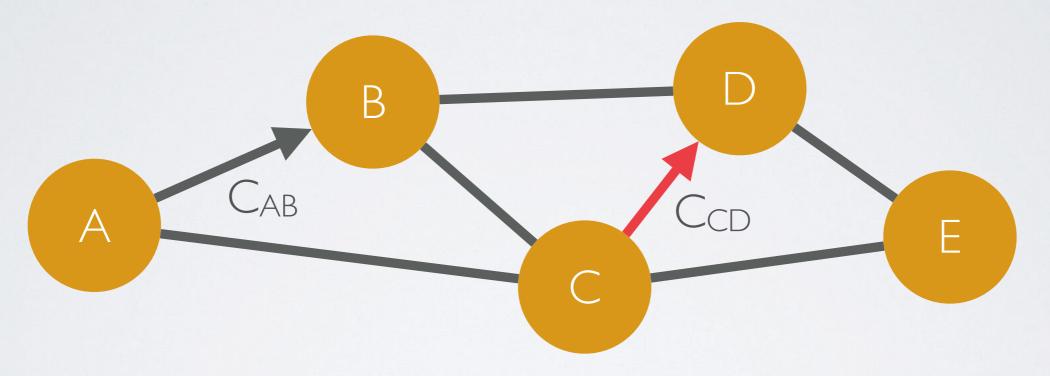
• Metric to measure interference



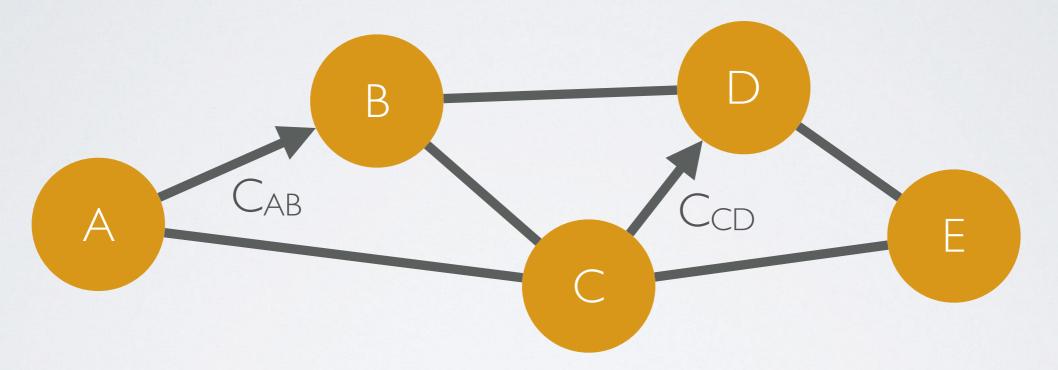
• Metric to measure interference



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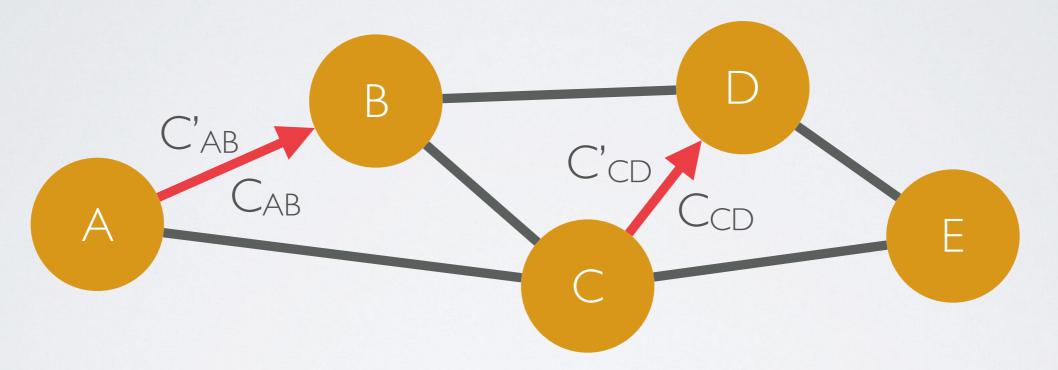


• Metric to measure interference

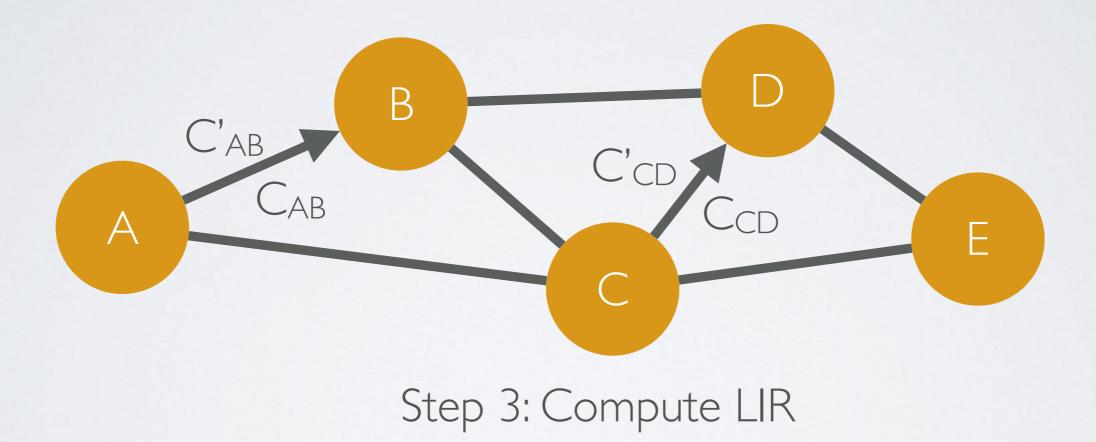


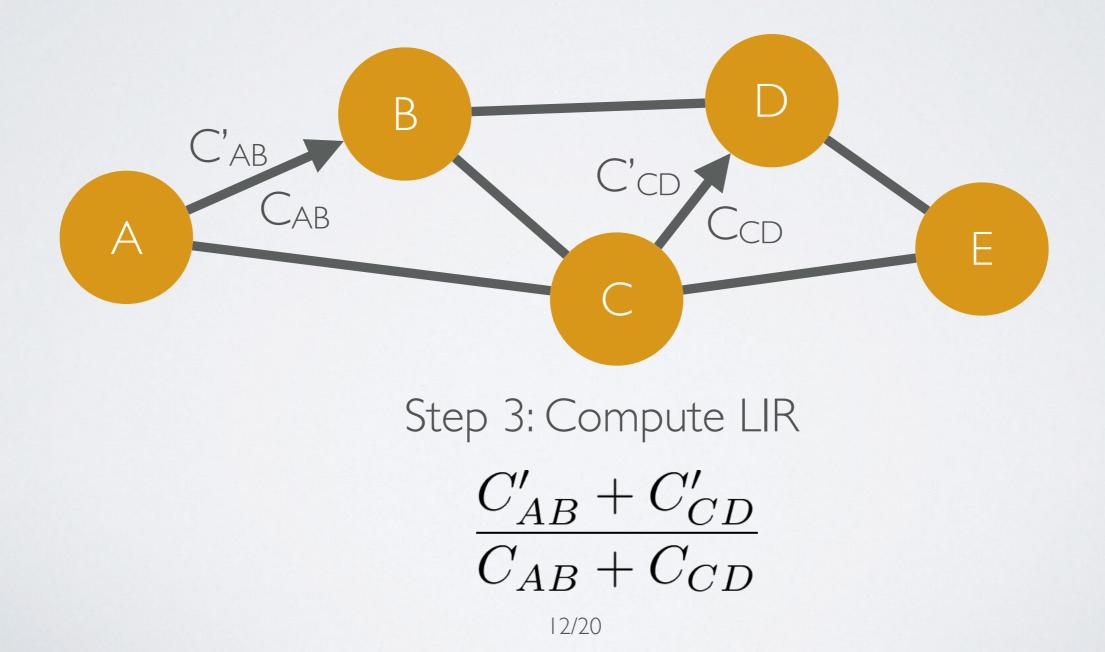
Step 2: Measure Individual Link Capacities Simultaneously

• Metric to measure interference



Step 2: Measure Individual Link Capacities Simultaneously

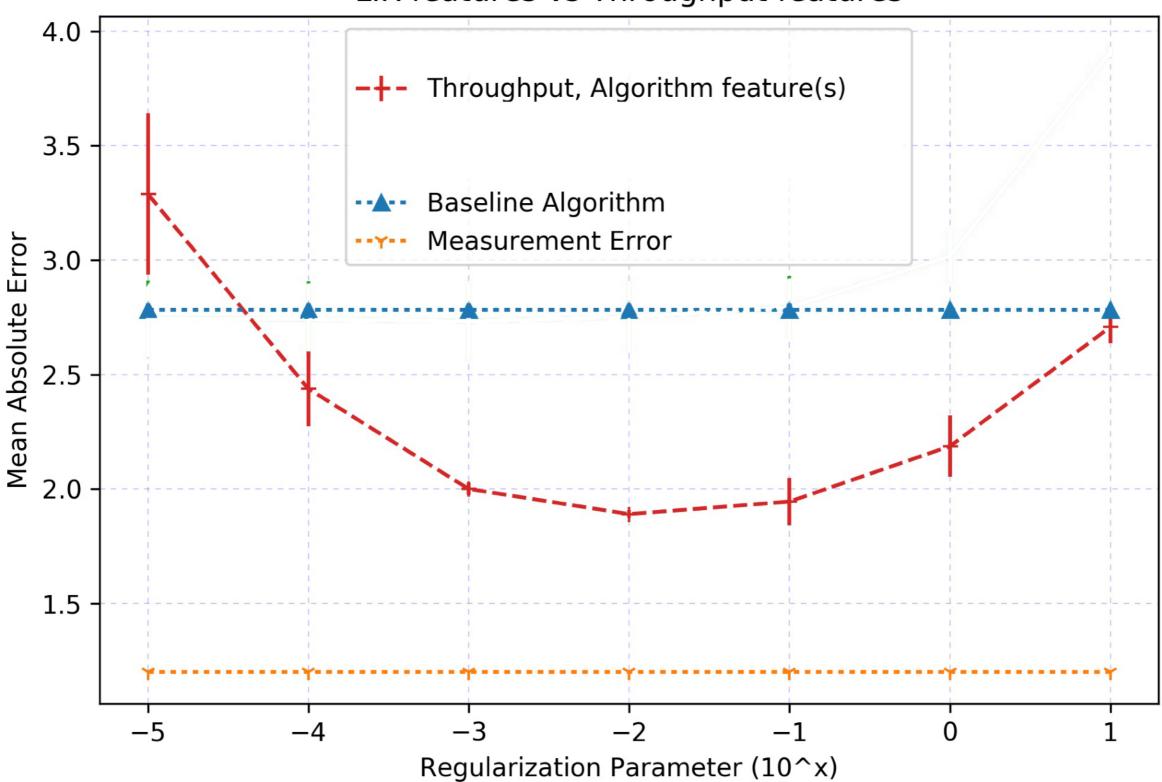




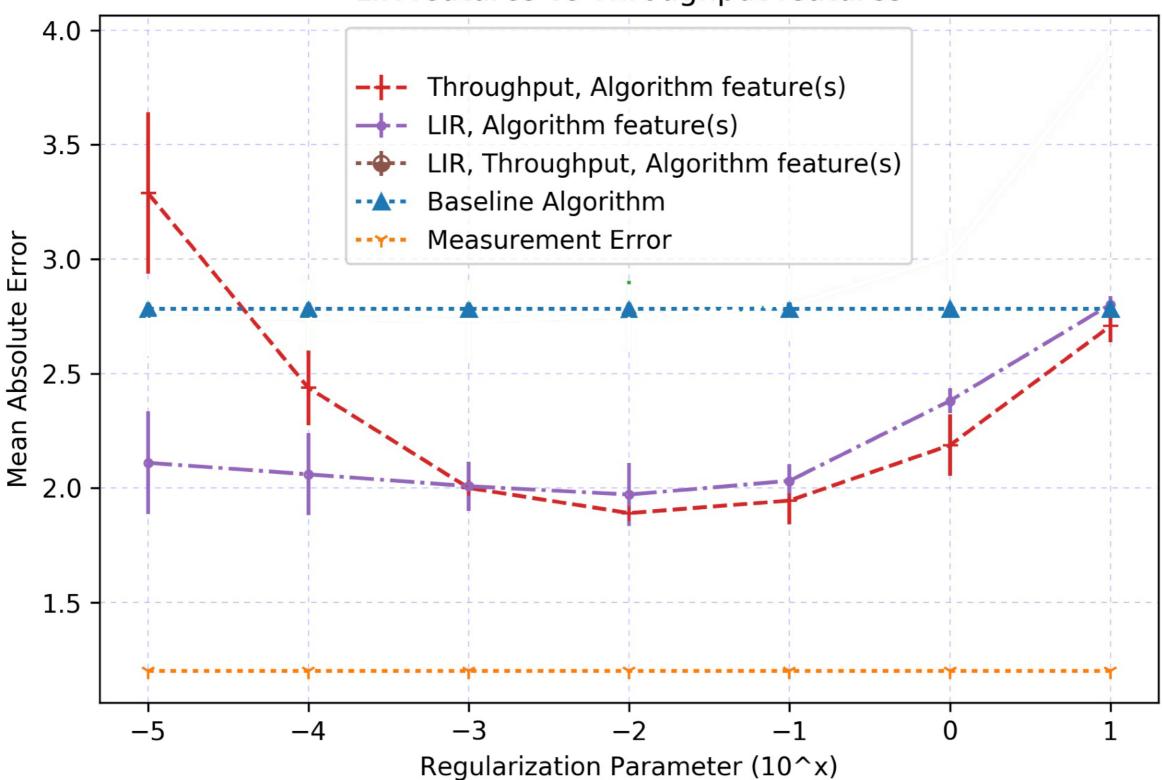
LIRVSTHROUGHPUT

- Requires n² measurements for an n node network.
- Throughput features require **n** measurements.

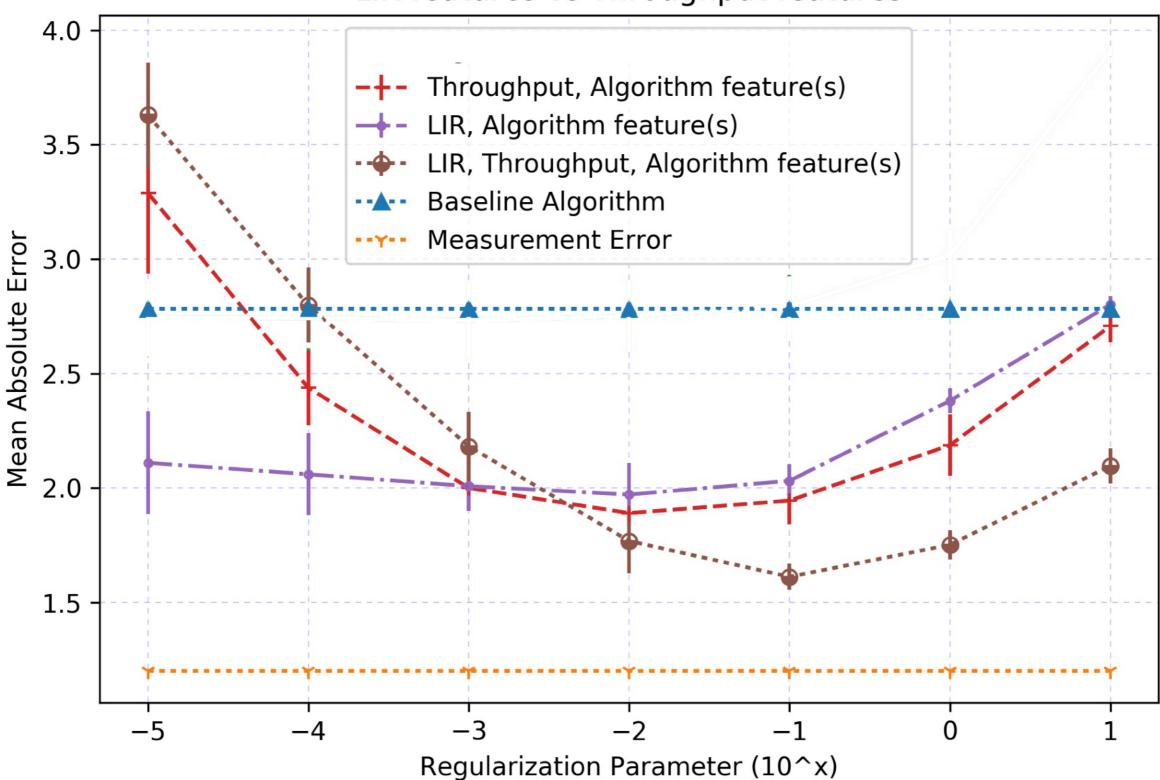
LIR features vs Throughput features



LIR features vs Throughput features



LIR features vs Throughput features



IDEA 3 : NETWORK WIDE FEATURES

[1] Grover, A., & Leskovec, J. (2016, August). node2vec: Scalable feature learning for networks. In *Proceedings of the 22nd ACM SIGKDD international conference on Knowledge discovery and data mining* (pp. 855-864). ACM.

IDEA 3 : NETWORK WIDE FEATURES

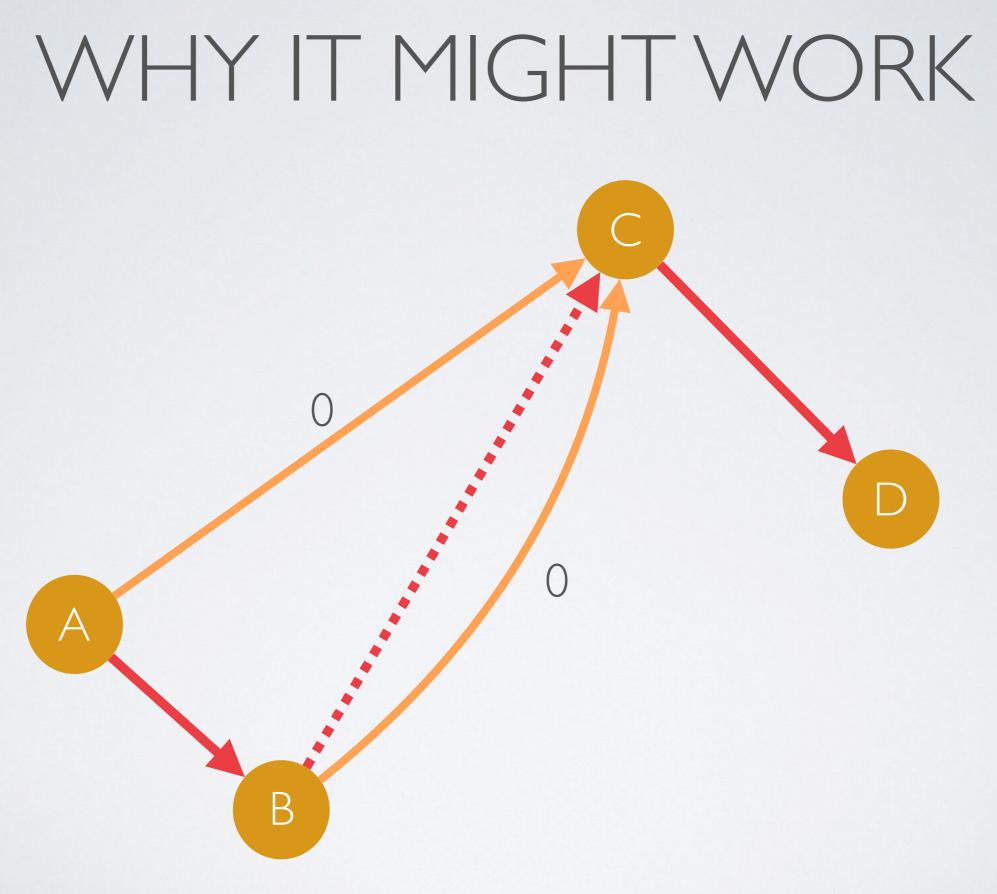
Node2Vec Embeddings¹

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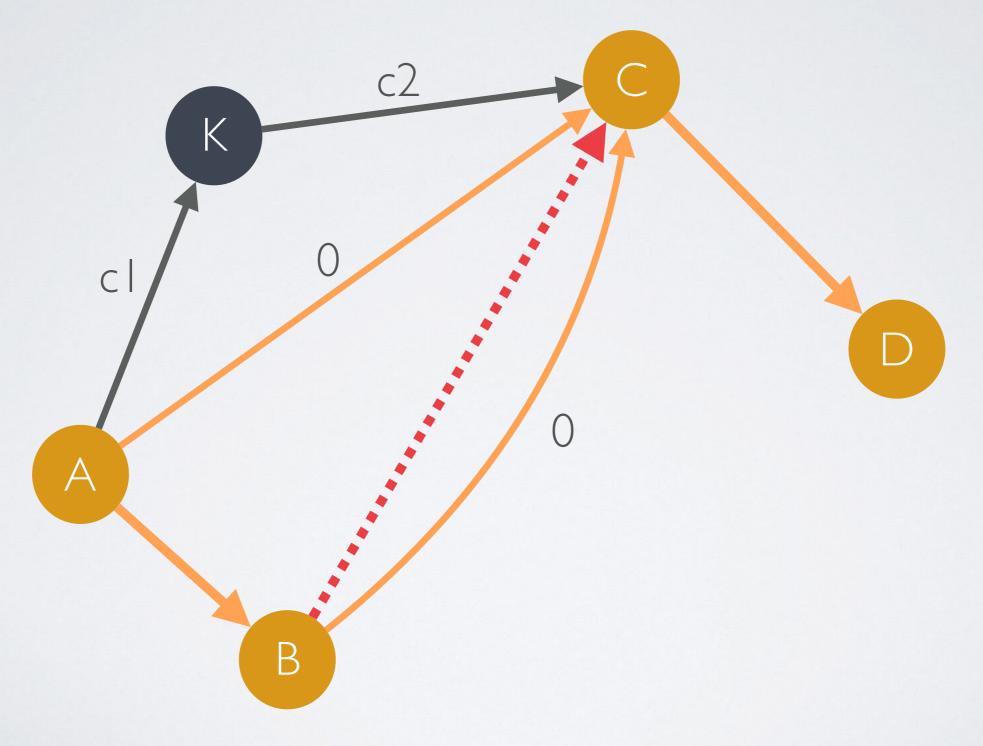
IDEA 3 : NETWORK WIDE FEATURES

- Node2Vec Embeddings¹
- Learn representations based on neighbors.

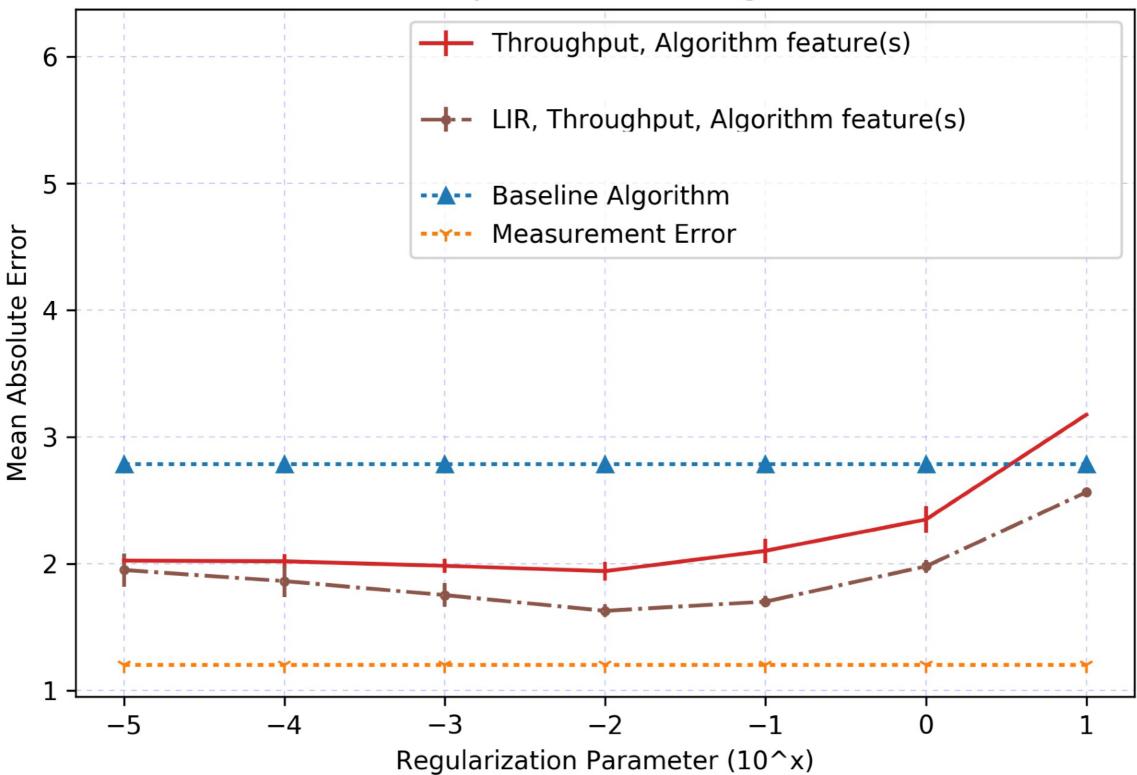
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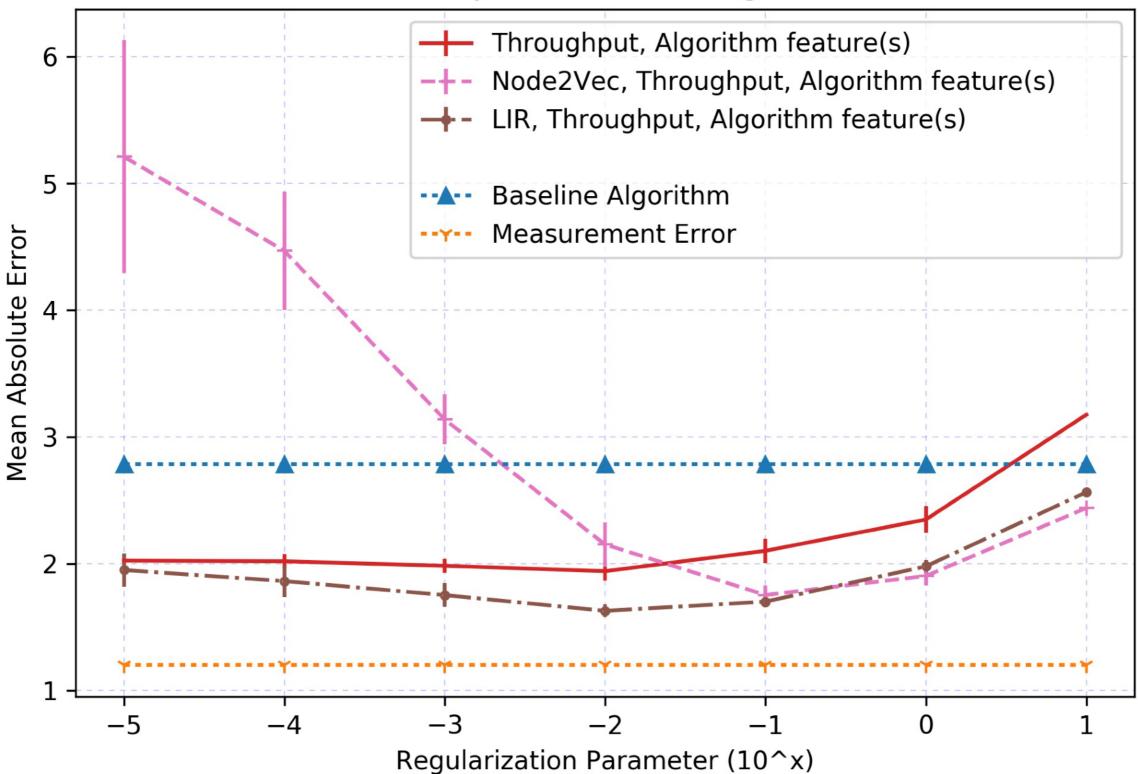




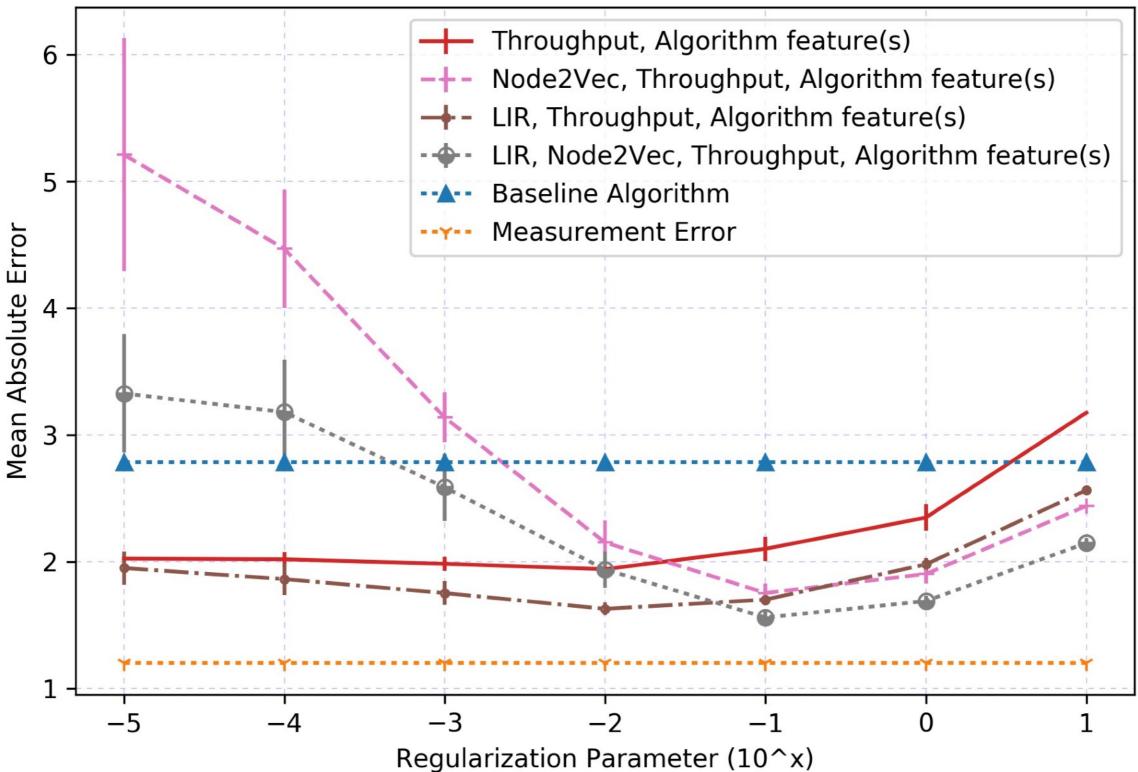
Impact of Embeddings



Impact of Embeddings

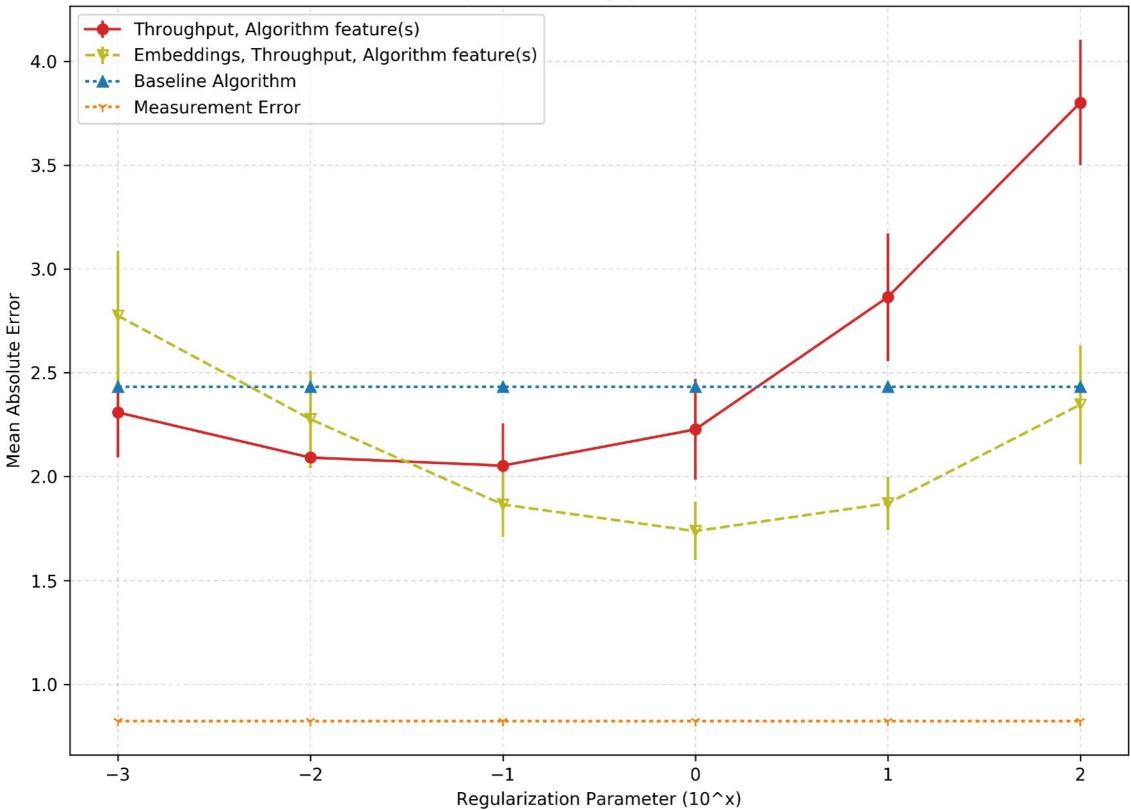


Impact of Embeddings



PWP Paths

Impact of Throughput Features



• Link capacities are useful!

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- LIR information is useful regardless of other features.

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- Interference patterns of PLC and Wifi are not identical.

CONCLUSIONS

- Link capacities are useful!
- LIR information is useful regardless of other features.
- Interference patterns of PLC and Wifi are not identical.
- We can learn from network-wide features.

• Exploring network wide features more.

- Exploring network wide features more.
- Understanding the reason behind differences in Wifi and PLC interference patterns.

- Exploring network wide features more.
- Understanding the reason behind differences in Wifi and PLC interference patterns.
- Moving towards practical predictions.

• Had an amazing summer.

- Had an amazing summer.
- Visited great places and met awesome people.

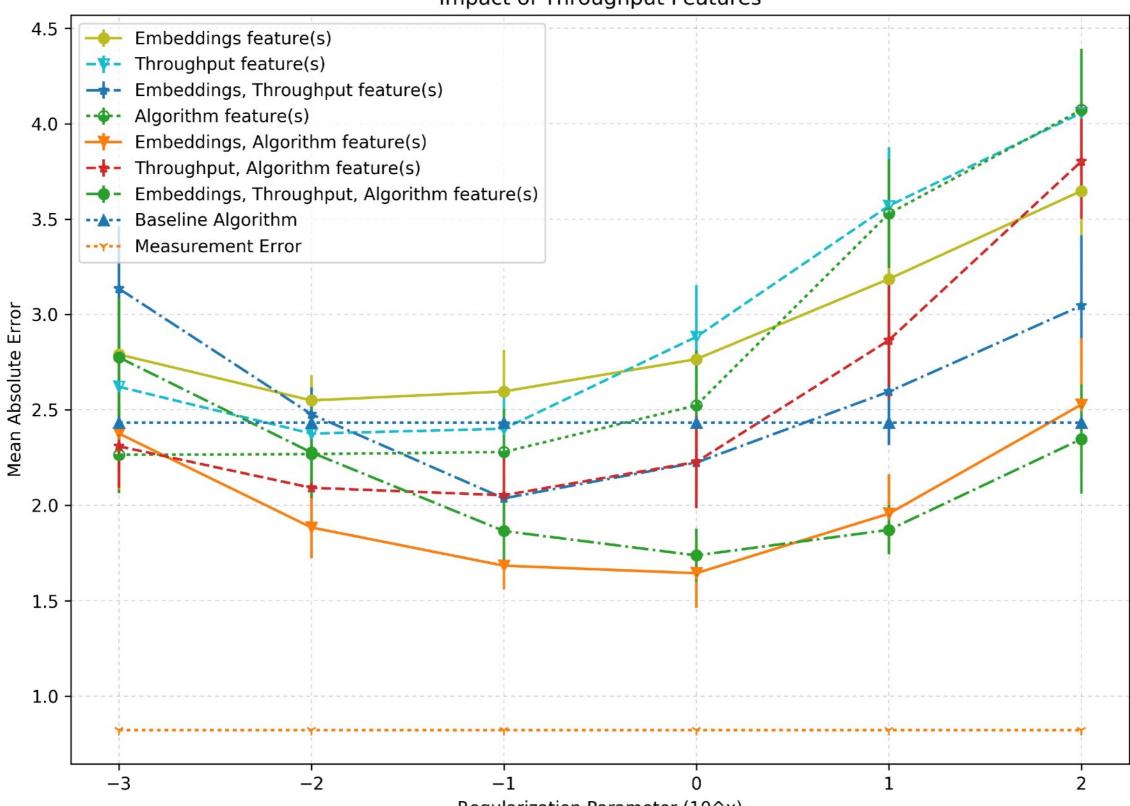
- Had an amazing summer.
- Visited great places and met awesome people.
- It was not 40°C for a change.

QUESTIONS?

- Input : Feature, Output : Path capacity
 - We collect data on a 22 node testbed using saturated UDP traffic.

- Input : Feature, Output : Path capacity
 - We collect data on a 22 node testbed using saturated UDP traffic.
- Non-linear model to test usefulness of information.
 - Data augmentation by varying Wifi transmission power.

- Input : Feature, Output : Path capacity
 - We collect data on a 22 node testbed using saturated UDP traffic.
- Non-linear model to test usefulness of information.
 - Data augmentation by varying Wifi transmission power.
- Finding important features.
 - Achieving similar results as non-linear models using linear regression.

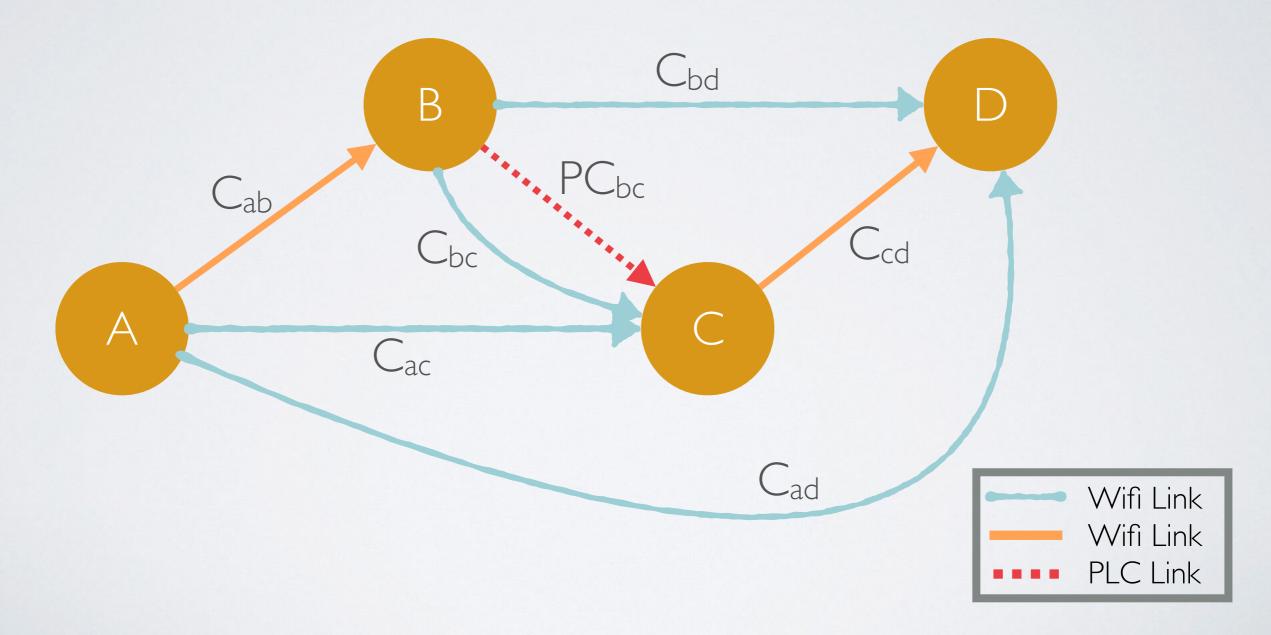


Impact of Throughput Features

Regularization Parameter (10^x)

• Does the magnitude matter? Yes; to some extent.

IDEA I : USE LINK CAPACITIES



• Does the magnitude matter? Yes; to some extent.

- Does the magnitude matter? Yes; to some extent.
- Can we understand what the model learns? Yes.