

# A Machine Learning Approach to Loss Differentiation Solution in 802.11 Wireless Networks

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**Sofia Pediaditaki and Mahesh Marina**


s.pediaditaki@sms.ed.ac.uk mmarina@inf.ed.ac.uk

**University of Edinburgh**



# Introduction

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- 802.11 Causes of Packet Losses:
  - Channel errors
  - Interference (collisions or hidden terminals)
  - Mobility, handoffs, queue overflows, etc.
- **How can a sender infer the actual cause of loss with:**
  - No or little receiver feedback
  - A lot of uncertainty (time-varying channels, interference, traffic patterns, etc.).
-  **Use machine learning algorithms!**

# Do we Need Loss Differentiation?

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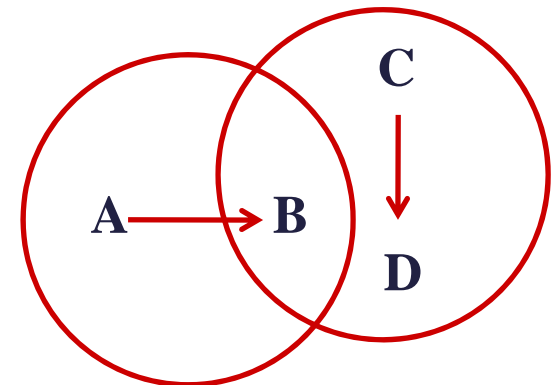
- **Rate Adaptation:**
  - Channel error → Lower rate improves SNR
  - Collision → Lower rate worsens problem
- **DCF mechanism:**
  - In 802.11, cause of loss is collision by default
  - Doubling the contention window hurts performance if cause is channel error
- Various other applications (e.g. Carrier sensing threshold adaptation [Ma et al – ICC'07])

# State of the Art

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## *Rate Adaptation Algorithms* [CARA-Infocom'06, RRAA-MobiCom '06]

- Use RTS/CTS to infer cause of loss
  - Small frames resilient to channel errors
  - Medium is captured → Data packet is lost due to channel error
- Drawbacks
  - RTS/CTS is rarely used in practice
  - Extra overhead
  - Hidden terminal issue not fully resolved
  - Potential unfairness



# Our Aim

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- A **general purpose** loss differentiator which is:
  - Accurate and efficient:
    - responsive and robust to the operational environment
  - Supported by commodity hardware
    - fully implementable in the device driver without e.g. MAC changes
  - Has acceptable computational cost and low overhead
  - Requires no (or little) information from the receiver

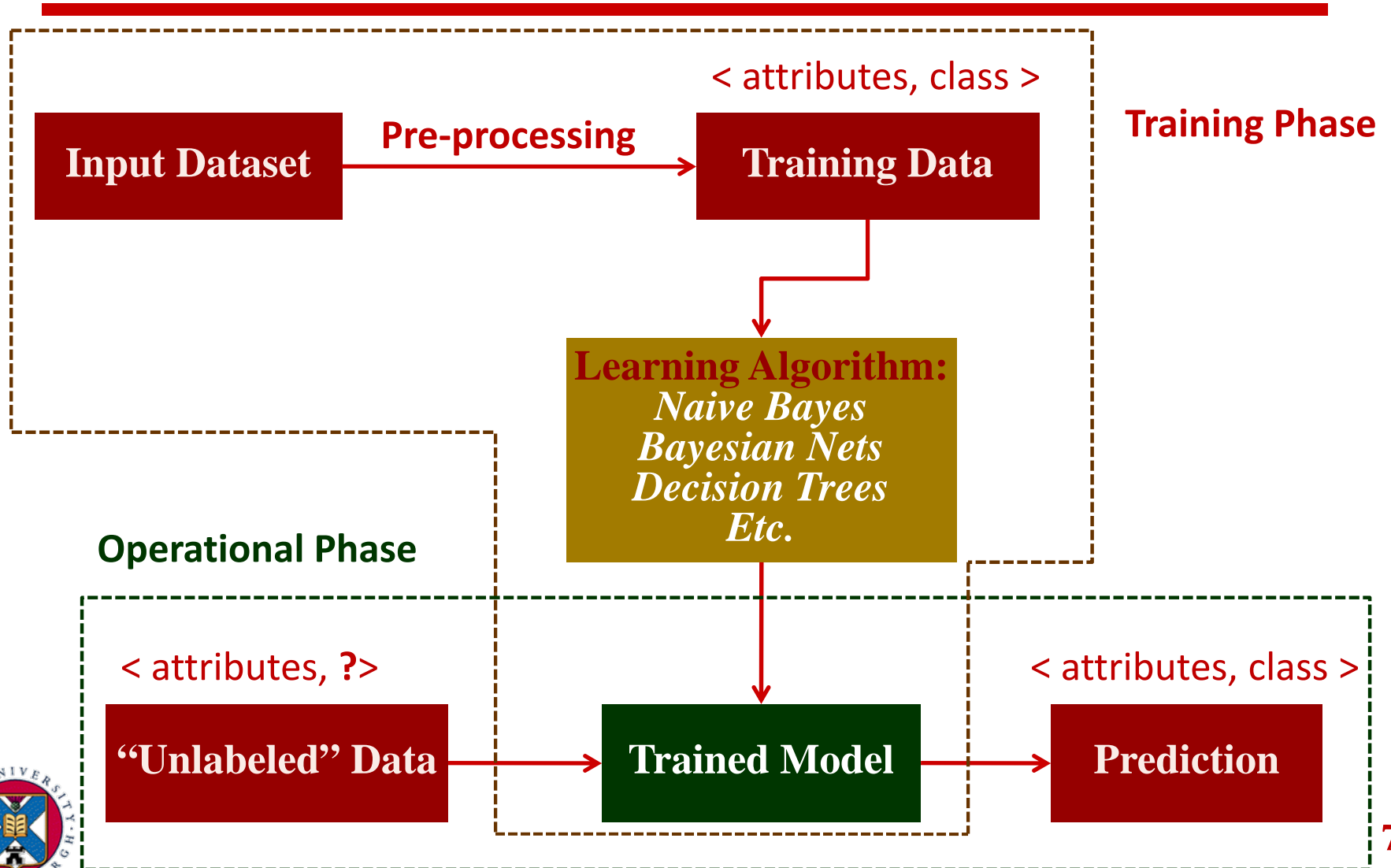
# The Proposed Approach

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- Loss differentiation can be seen as a “**classification**” problem
  - *Class labels*: Types of losses
  - *Features*: Observable data
  - *Goal*: Assign each error to a class
- *The Classification Process*:
  - Training Phase:
    - $\langle \text{attributes, class} \rangle$  pairs as training data
  - Operational Phase:
    - Classify new “unlabeled” data (test data)



# The Classification Process



# Performance Evaluation (1/2)

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- Training data using *Qualnet* Simulator
  - Single-hop random topologies (WLANs)
    - Varying number of rates and flows , with or without fading
  - Multi-hop random topologies
    - One-hop traffic, multiple rates, with or without fading
- Learning algorithms using *Weka* workbench  
(*University of Waikato, New Zealand*)
- Classes of interest:
  - Channel errors
  - Interference



# Performance Evaluation (2/2)

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- **Classification Features:**

- Rate

- The higher the rate, the higher the channel error probability

- Retransmissions No

- Due to backoff, collision probability decreases across retransmissions

- Channel Busy Time

- Observed channel errors and collisions

**Easily obtained at the sender**



# Preliminary Results: **No fading**

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**Try the simple things first (K.I.S.S. Rule)!**

<b>Bayes Method</b>	<b>Prediction Accuracy%</b>		<b>Training Time (sec)</b>
Naive Bayes	<b>WLAN</b>	<b>WLAN-MH</b>	0.01
	99.5	95.9	

- 29303 WLAN – 55140 WLAN-MH instances
- 10-fold Cross Validation
- Almost perfect predictor
  - But things are not that simple!



# Preliminary Results: **All together**

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**A small step for man ...**

<b>Bayes Method</b>	<b>Prediction Accuracy%</b>	<b>Training Time (sec)</b>
Naive Bayes	87	0.06
Bayesian Net	87.7	0.15

- 125213 instances
- 10-fold Cross Validation
- Naive Bayes assumes attributes are independent
- Bayesian Networks make Naive Bayes less “naive”



# Discussion

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- Which machine learning algorithm is more appropriate to use?
- Which features are the most representative?
- Is this solution generalizable?
- Can we use the solution as it is in real hardware?
- How much training is it required?
  - What if we use semi-supervised learning?

# Summary

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- Why do we need a loss differentiator:
  - Rate adaptation algorithms, 802.11 DCF mechanism, ...
- We propose a machine learning-based predictor
  - Handles loss differentiation as “classification” problem
- There are still many things do be we should consider...
- So, can we use such solution?
  - Yes, we can [Obama '08]
  - Preliminary results show we could 😊



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# Thank you

Questions?

