domain knowledge

gaurav and suriyan

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  - you can have your *cookie* and eat it too!

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Considerations

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- accuracy

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  compare with Alexa 1M to build classifiers that can tell those apart

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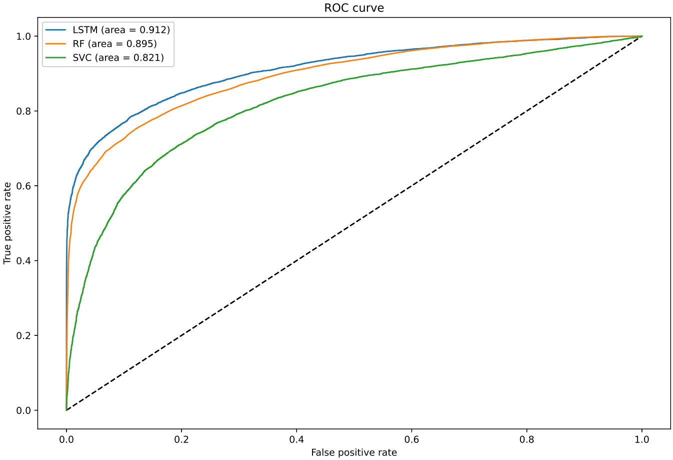
  - LSTM


ROC curve
LSTM (area = 0.912)
RF (area = 0.895)
SVC (area = 0.821)
True positive rate
False positive rate
0.0
0.2
0.4
0.6
0.8
1.0

PhishTank

Application

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- Are disadvantaged people most at risk online?

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Data

Application

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- comScore panel

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Data

- comScore panel
- domain level data for a machine in a household + household attributes

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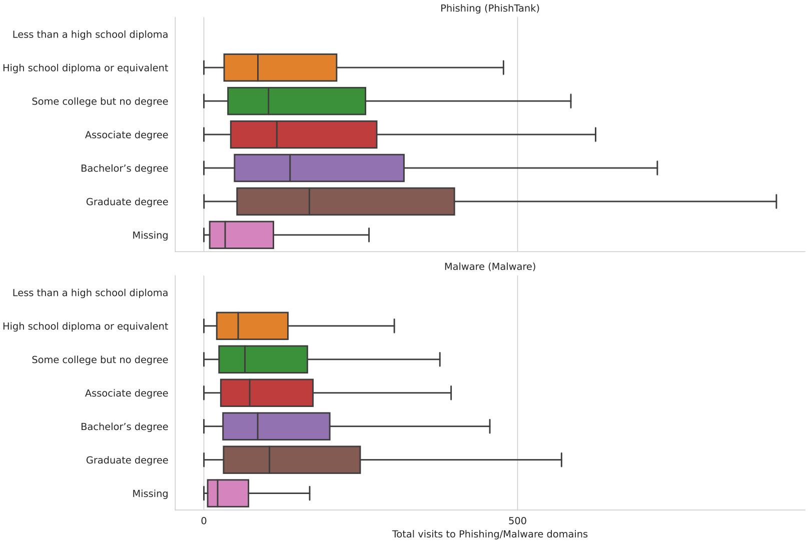
Solutions

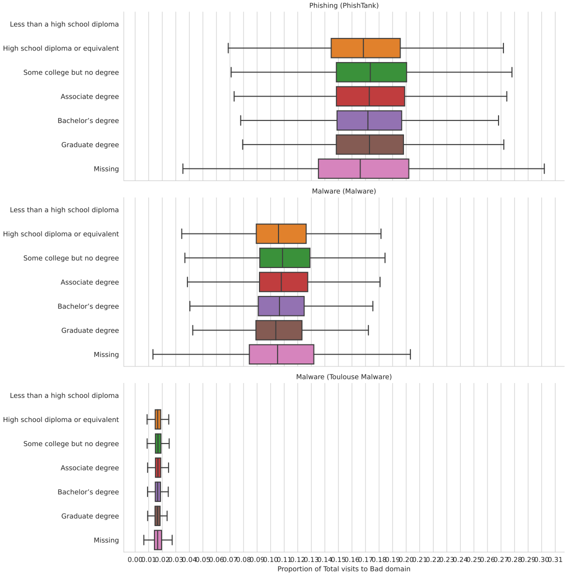
- Calibration $\rightsquigarrow$ $FP = FN$ locally
- Using curated lists (manual coding) for popular domains

The better educated visit phishing/malware domains most often



Visits to phishing/malware domains

But the less educated choose worse



Proportion of visits to phishing/malware domains