Early online classification of encrypted traffic streams using multi-fractal features

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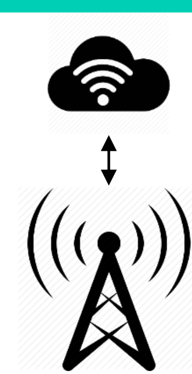

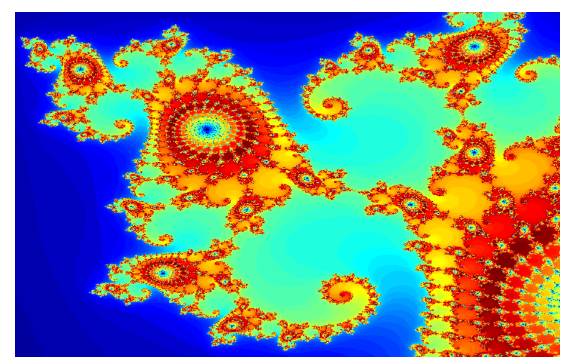

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- End-to-end encryption render traditional deep packet inspection techniques useless
- Most flow classification approaches are unable to properly capture the non-linear characteristics of network flows
- Problem: Current classification methods are too slow or inaccurate to benefit network operators

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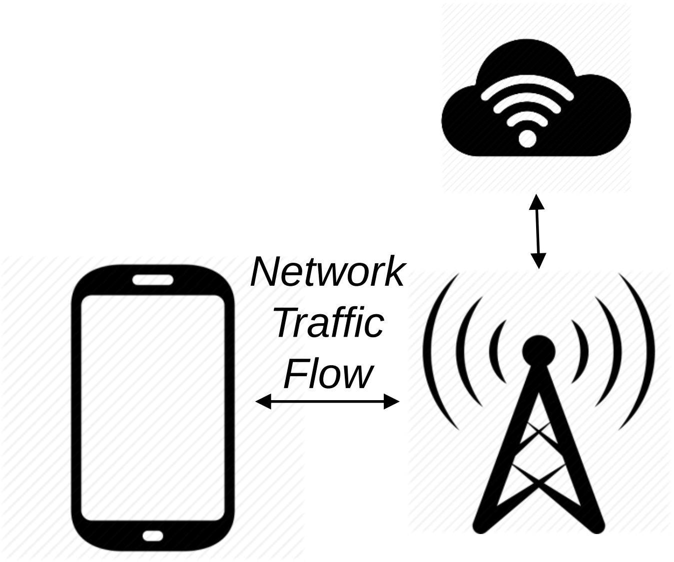
- Early traffic categorization via tuning of said framwork achieving F1-scores of 0.814 after only 5 seconds, using only multi-fractal features
- In-class categorization of live video versus video on demand delivered from the same services, using only multi-fractal features

High-level categorization

Application categories	Example service
Video streaming	Youtube
Web browsing	Reddit
Social media	Facebook
Audio communication	Skype
Text communication	Messenger
Bulk download	Google Play

System model



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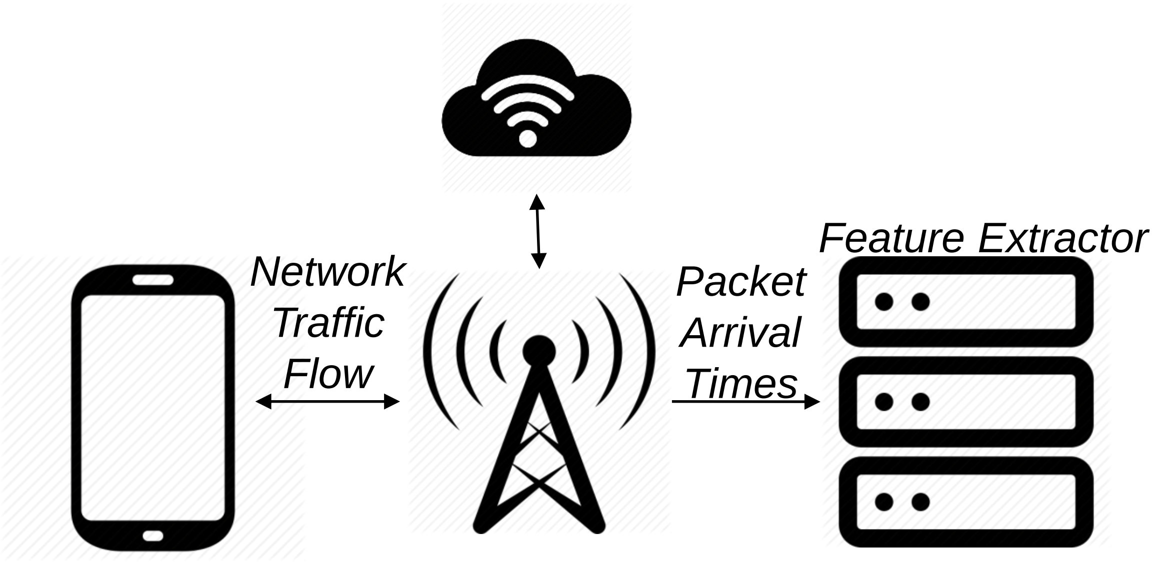

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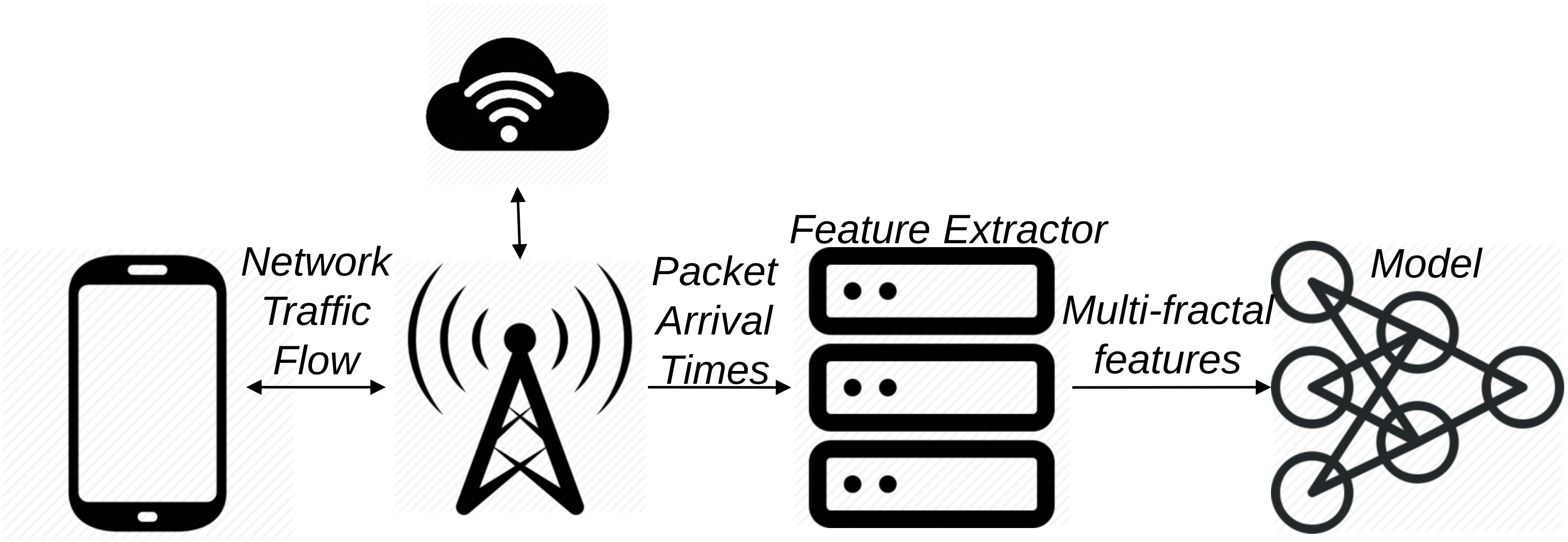

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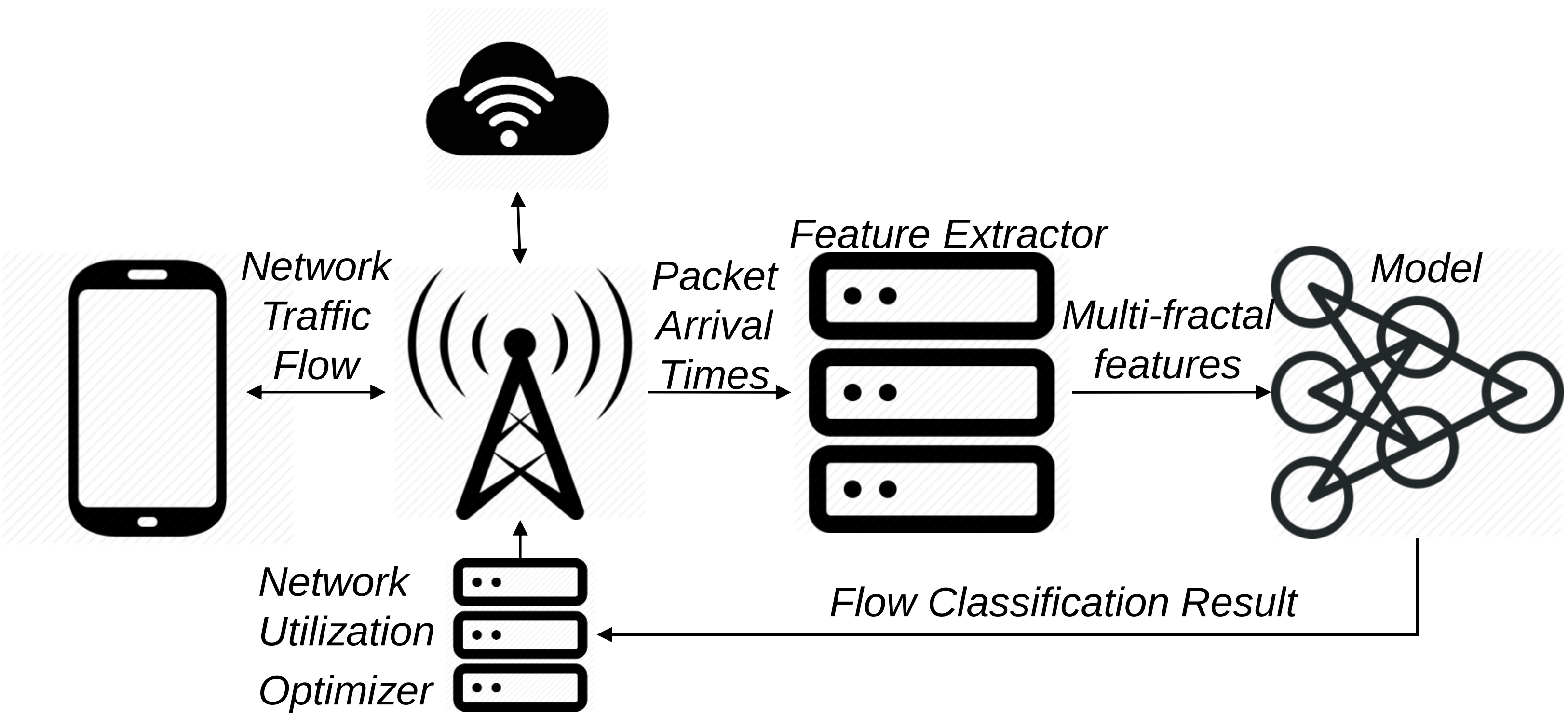

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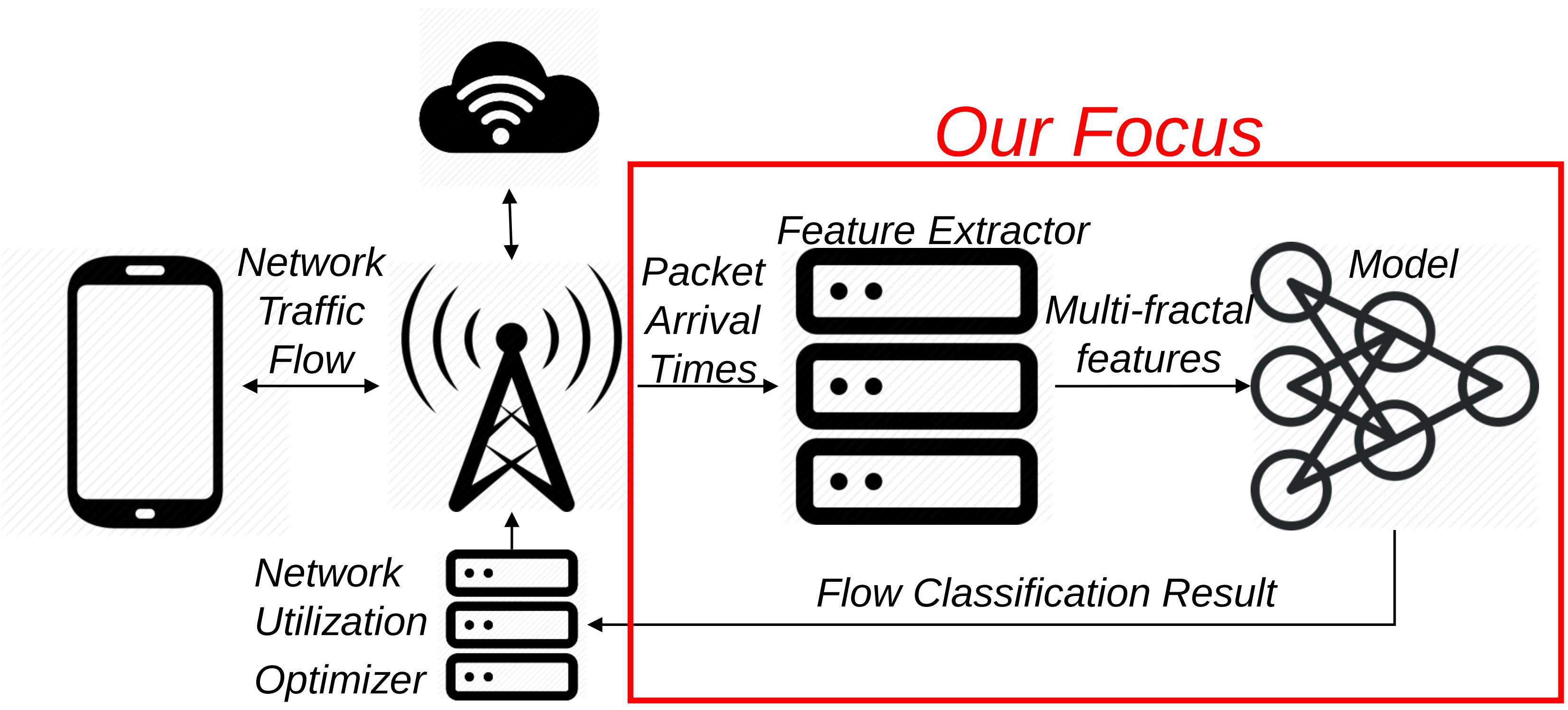

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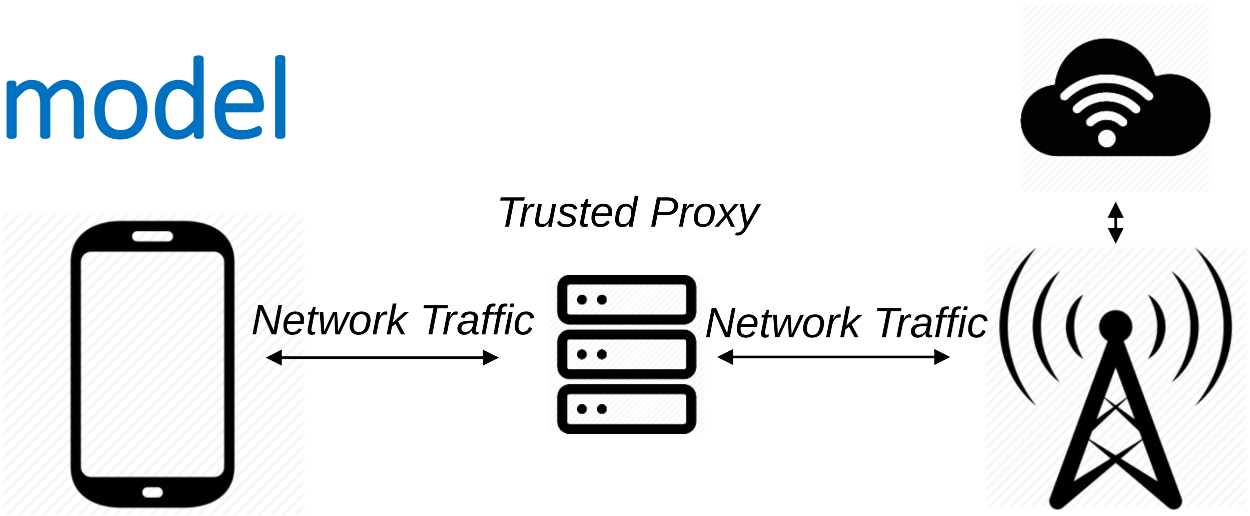

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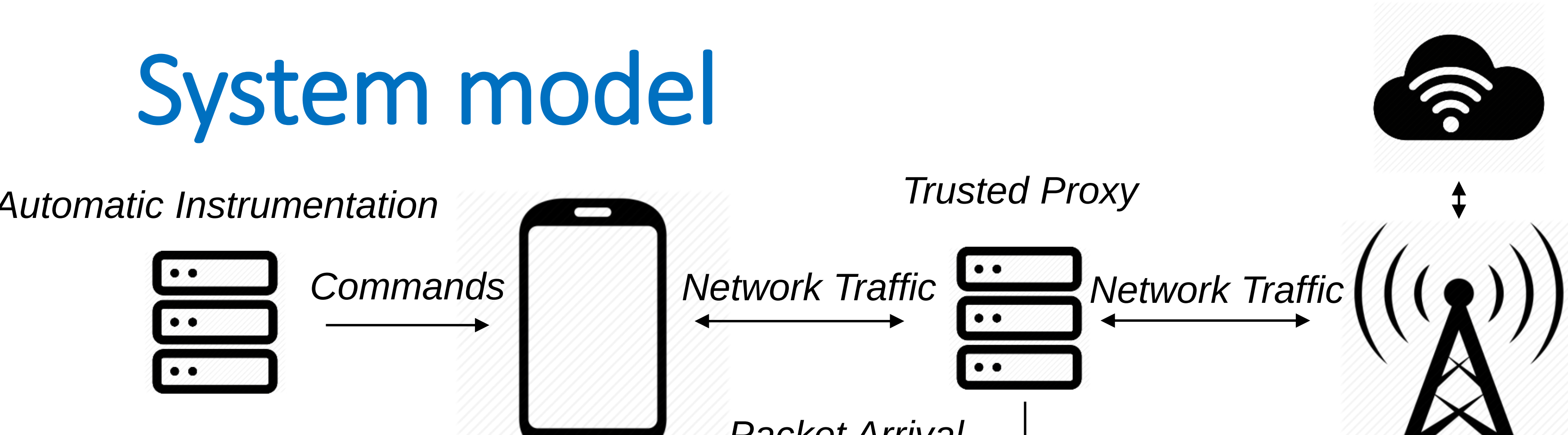
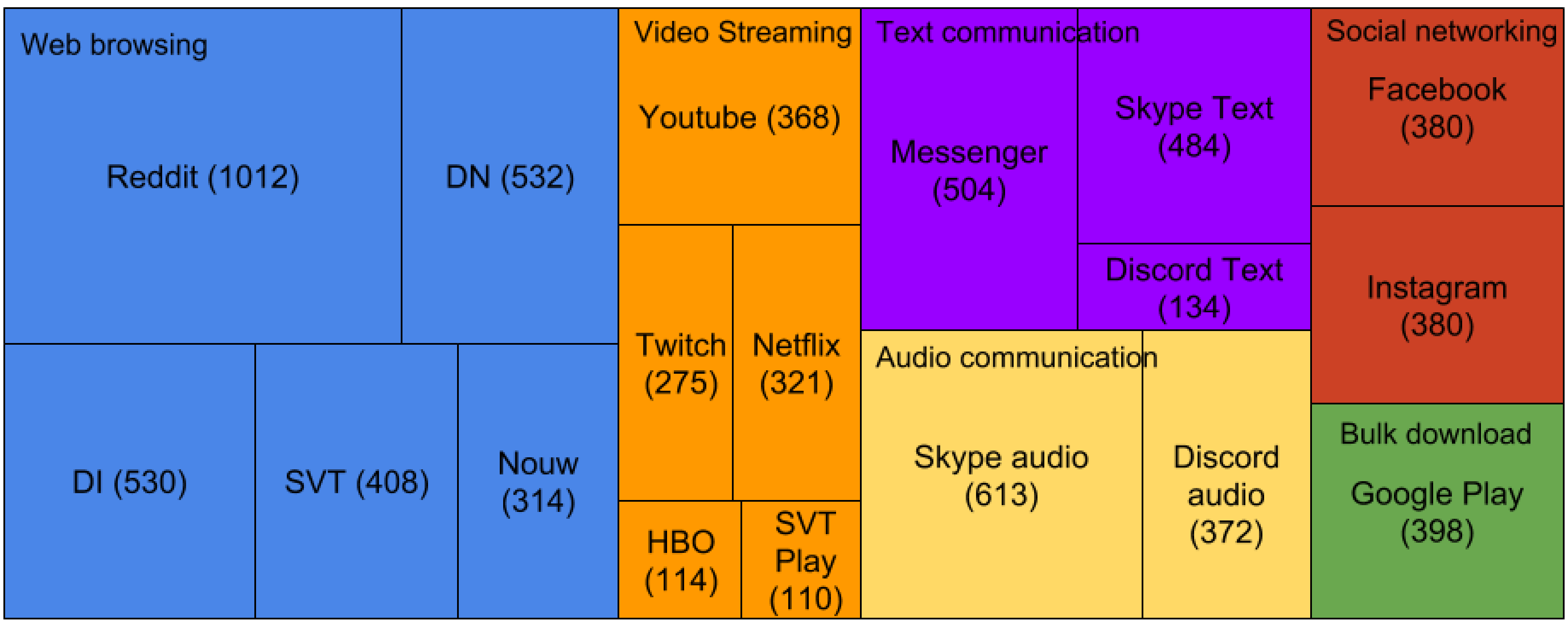


The samples



Feature extraction

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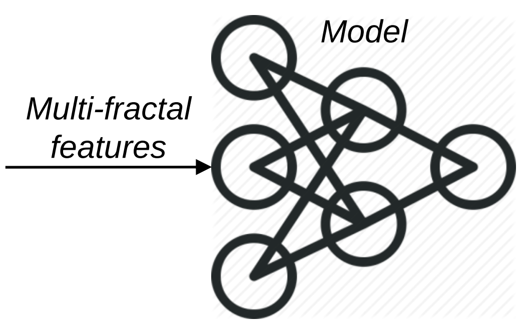
The multi-fractal features, representing how the observed self-similiarty of the signal changes over time

Building the model

- The collection of samples were randomly split into two parts, half the samples were used to build the model



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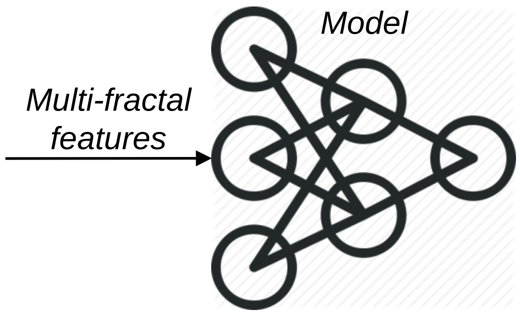
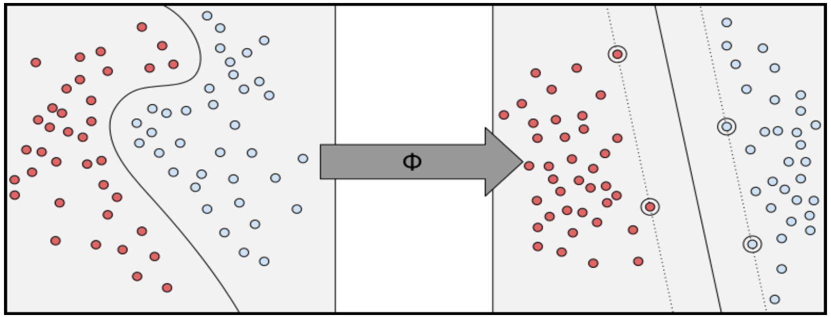
- The collection of samples were randomly split into two parts, half the samples were used to build the model
- Multiple Binary Support Vector Machine classifiers were used, fitting the maximun margin separating hyperplane between each class of data



SVM with radial basis kernel function



Evaluation (t = 20 s)

	Audio Com.	Bulk Down.	Text Com.	Social Media	Video	Web	**Precision**
Audio Com.	4847	6	9	11	5	24	0.989
Bulk Down.	5	1949	8	5	4	0	0.989
Text Com.	59	1	5389	7	3	152	0.960
Social Media	2	1	12	3459	49	308	0.903
Video	5	2	10	175	5251	95	0.948
Web	2	1	192	143	178	13441	0.963
Recall	0.985	0.994	0.959	0.910	0.956	0.959	0.960

Targeted class

Output class

Class	F1-score
Audio Communication	0.98
Bulk Download	0.99
Text Communication	0.96

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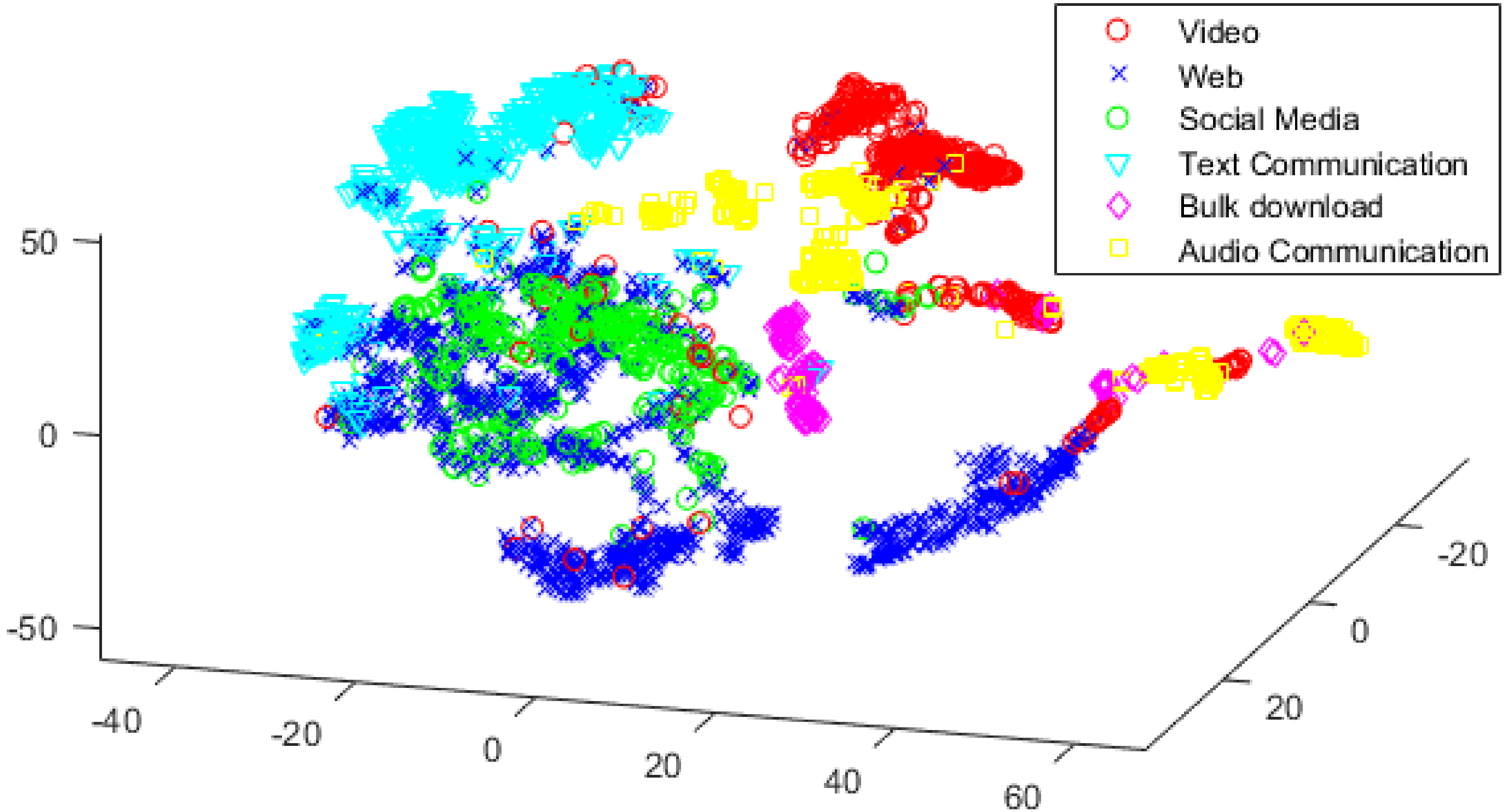
T-SNE visualization



Early classification

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2.5 seconds	0.631	0.594	0.673

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2.5 seconds	0.631	0.594	0.673
2 seconds	0.409	0.404	0.415
1 second	0.214	0.202	0.228

Randomly picking one category: 1/6 ≈ 0.167

Impact of added variance in the dataset.

- All packet arrival instances in the evaulation set were perturbed according to a normal distribution:

$$\mathcal{N}(0, \sigma)$$

σ	10	25	50	100	250	500	1000
F1-score	0.952	0.942	0.925	0.927	0.891	0.834	0.695

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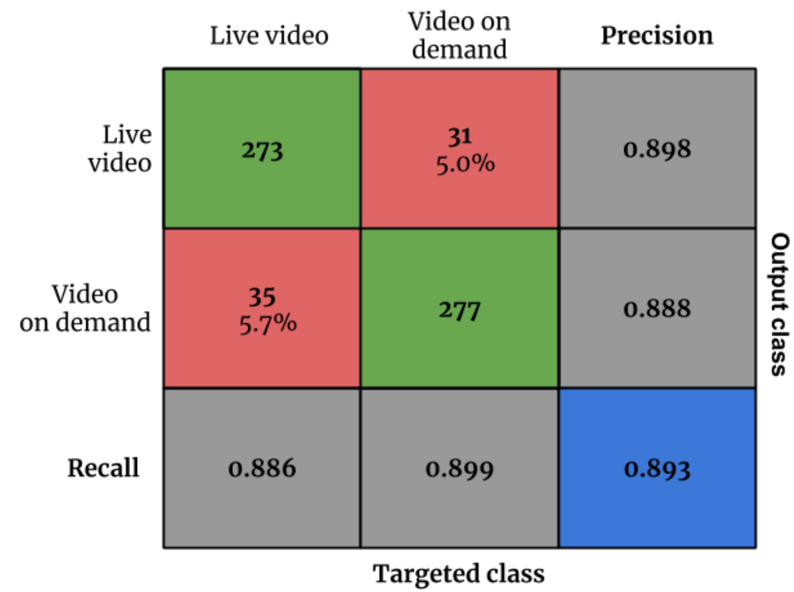
31.8% of the packets arrivals move by more than ± 0.5 seconds

In-class categorization, live vs VoD

- Same IP addresses may be used for both live and VoD content, categorization needs to be done online



Category	Live	Vod
Samples	616	616
Class Composition	Youtube: 214 Twitch: 214 SVT Play: 188	Youtube: 214 Twitch: 214 SVT Play: 188

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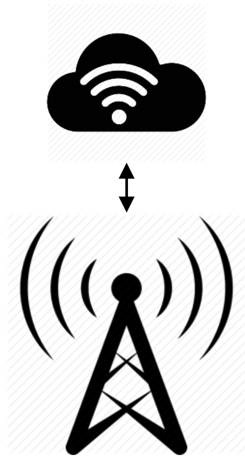
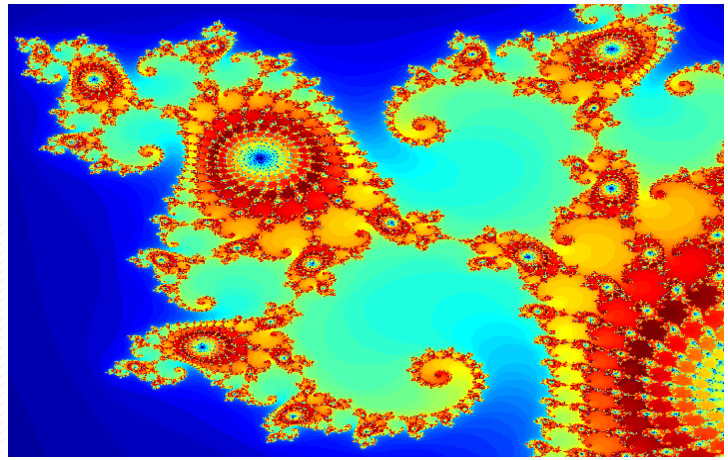
- The method relies only on access to timing information of the packets in a flow and is highly resistant to perturbations of this information
- The method can be applied to distinguish between classes of data belonging to the same services (Vod and live streaming)

Thanks for listening!





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