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Few Shot Learning Approaches for Classifying Rare Mobile-App Encrypted Traffic Samples

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Mobile-App Traffic Classification

- **Deep Learning (DL)** is effective for classifying encrypted network traffic
 - But it requires large amounts of labeled data to provide satisfactory results
- Collection of large labeled network-traffic datasets
- Number of new apps constantly rising (4.67 million apps during the last quarter of 2021¹)



¹Number of available apps in the Google Play Store from 2nd quarter 2015 to 2nd quarter 2022 - www.statista.com

Mobile-App Traffic Classification: Issues

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 - Time-consuming process
 - User-privacy and business-sensitivity concern
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Often only a
few labeled traffic samples
are available

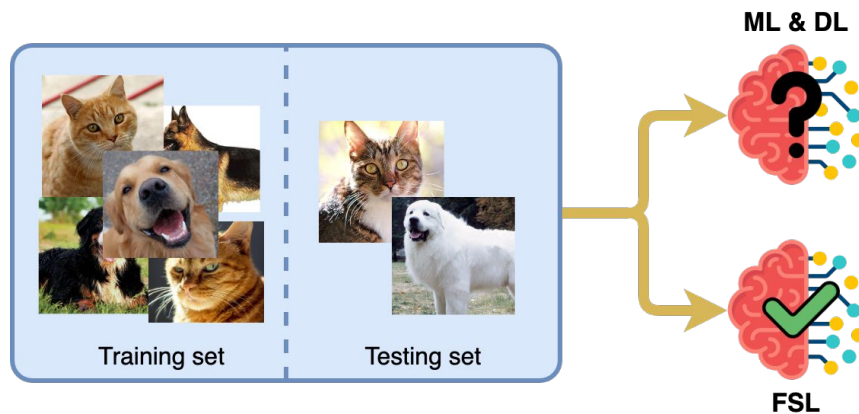


Adoption of
DL falls short



Few-Shot Learning

Few-Shot Learning (FSL) aims at tackling this issues, by leveraging non-few knowledge (prior knowledge) in order to build a **model capable of generalizing** enough on new tasks **with few samples available**



Research questions

- Can be **FSL approaches** applied to the **mobile-app encrypted traffic classification**?
 - ... and how to tailor it to this domain?
- What is the impact of using different **FSL setups** in terms of **number of training classes N** (viz. Apps) and **number of shots K** (viz. biflow for each App)?

N-way K-shot setup



Few-Shot Learning: Paradigms

- **Transfer Learning**

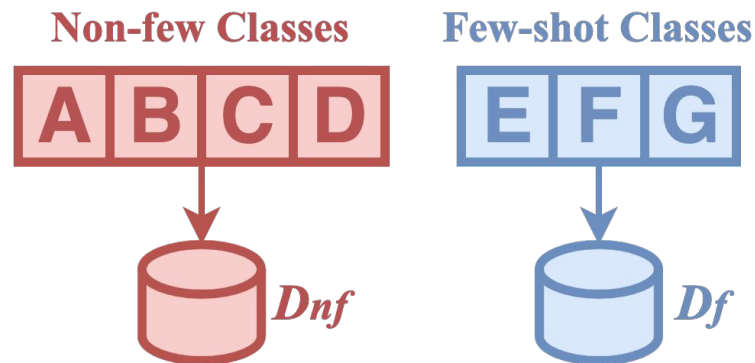
- Aims to *transfer knowledge* from a task to a related one with the objective of **fast adaptation, reduced complexity, and performance improvements**

- **Meta Learning**

- It is the ability of "**Learning to learn**" or *learning to compare*
- The ultimate goal is to provide a **model capable of generalizing** enough on tasks with **unseen classes**

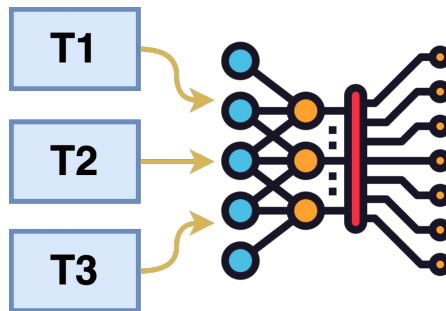
Preliminary: Dataset Partitioning

- The most populated classes are *separated from* the less populated ones
 - Most populated classes are included in the training set D_{nf}
→ used for **training**
 - Less populated classes are included in the testing set D_f
→ used for **testing**



Transfer-Learning Approaches

- The Transfer-learning approaches use prior knowledge (D_{nf}) to learn a **good initialization point** for the model weights, i.e. *base model*
- The base model is **adapted** to *classify few-shot classes* (D_f)
 - Done via **fine-tuning** to different extents

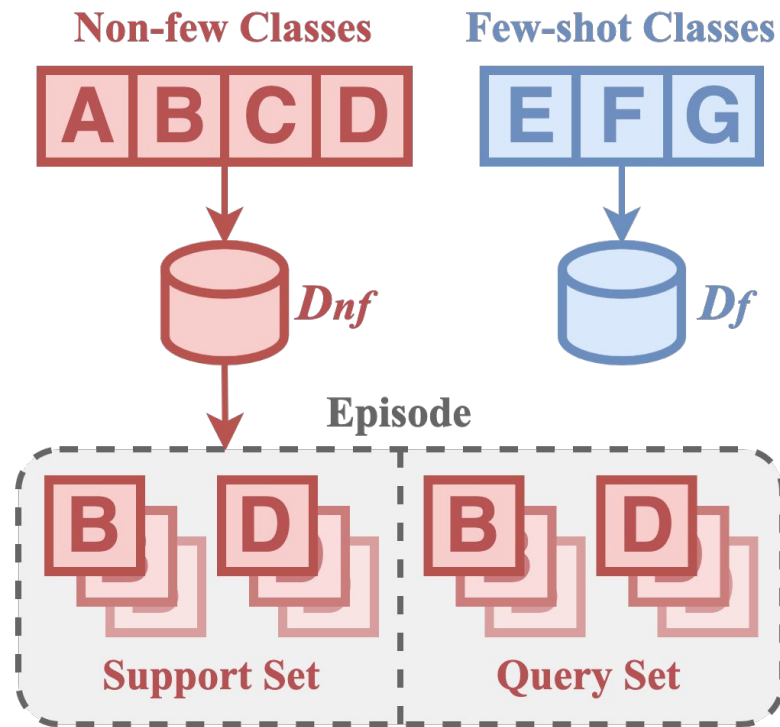


Meta Learning: Episodic Learning

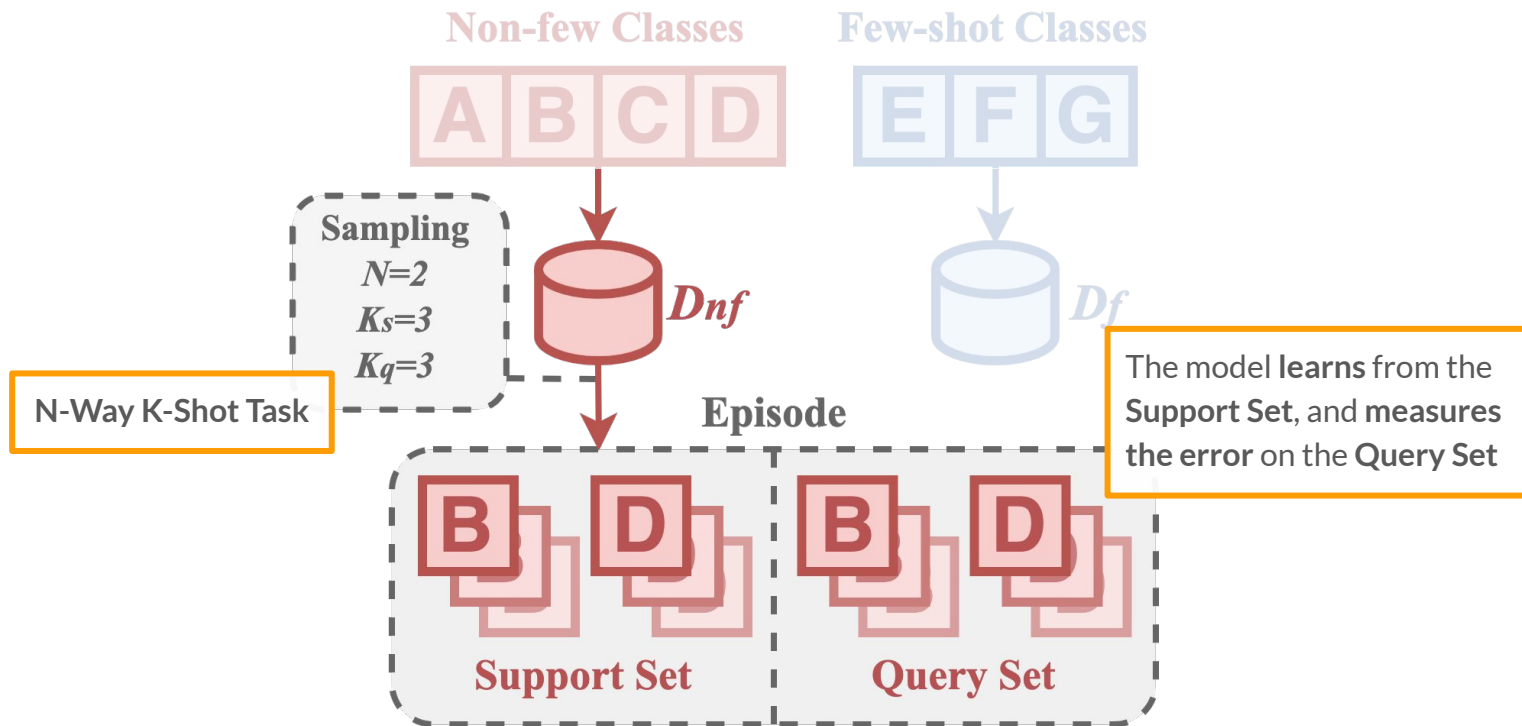
The meta learning is used jointly with episodic learning

Episodic Learning

- Training is organized as series of learning problems (**episodes**)
- Episodes mimic the **inference** scenario

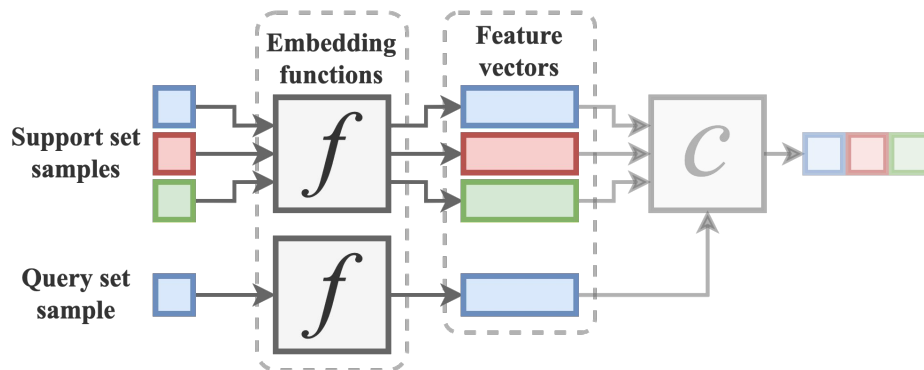
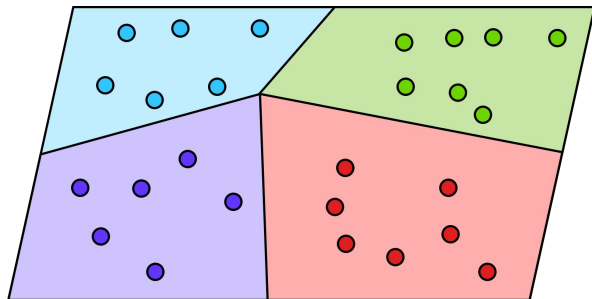


Meta Learning: Task Configuration



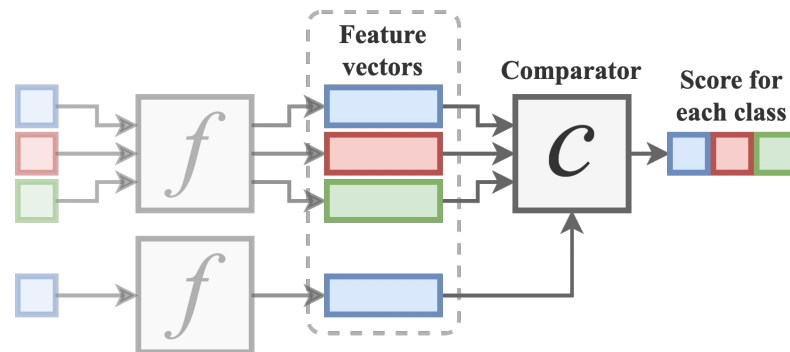
Meta-Learning Approaches

- Prior knowledge (D_{nf}) used to train an embedding function (f)
 - *similar* samples are *closer* to each other
 - *dissimilar* samples are more *easily separable*
- Doing so they manage to **reduce the hypothesis space complexity**



Meta-Learning Approaches

- Classification is performed by measuring the similarity of support and query feature vectors through a **comparator** (c), e.g., k-NN, SVM, NN.
- The output of the comparator is a **similarity score**
- Model-based methods **differ** according to the comparator



Experimenting with FSL: Dataset

- **MIRAGE-2019**

- Collected at ARCLAB University of Napoli Federico II from May '17 to May '19
- Publicly available (scan the code!)
- **Human-generated** dataset (~300 users)
- **40** popular Android / **16** different app categories
- **Biflows** as traffic object

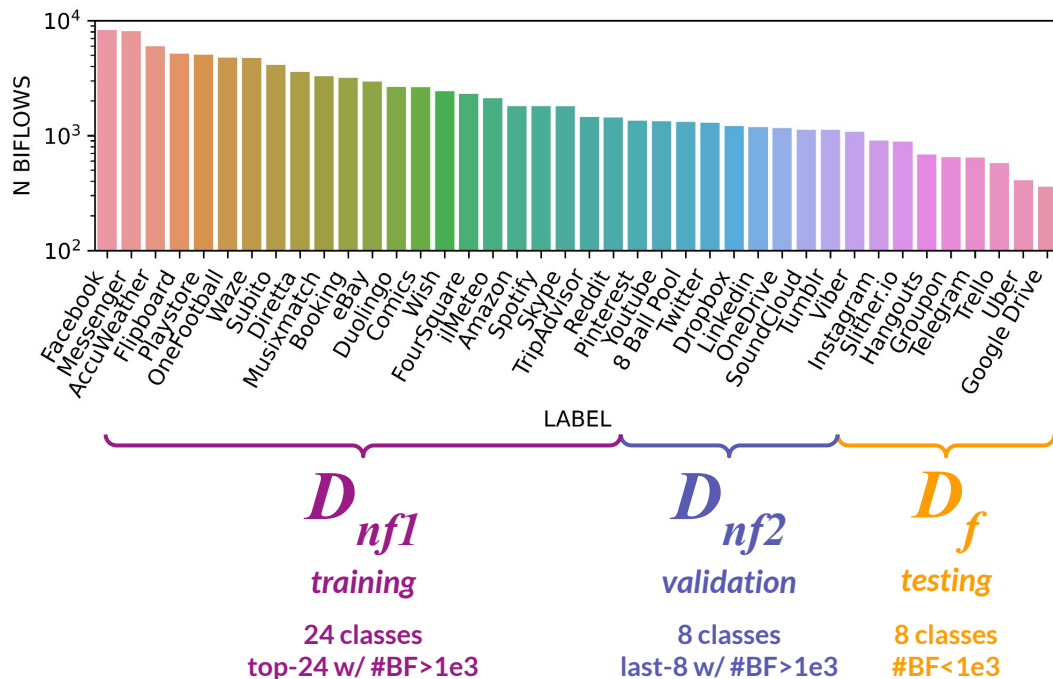
MIRAGE-2019 dataset is available at



<https://traffic.comics.unina.it/mirage>

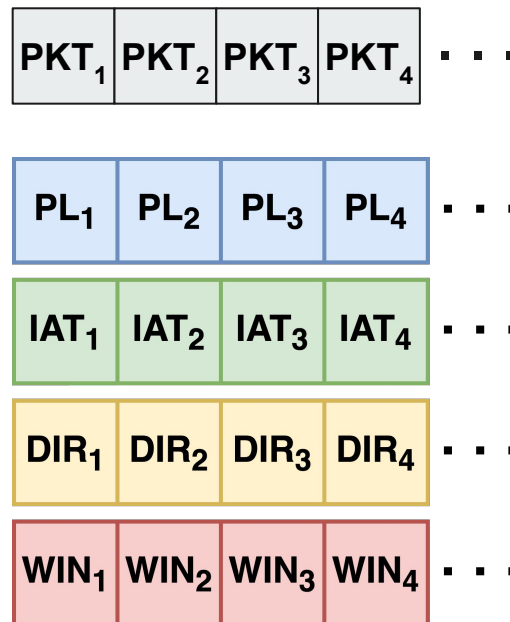


Experimenting with FSL: Dataset Partitioning

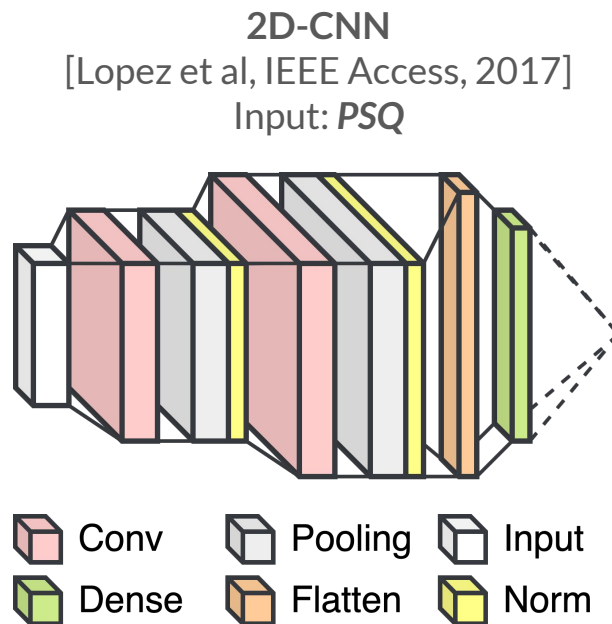


Experimenting with FSL: Input Data

- **PSQ**: informative fields of the first $N_p = 10$ packets of each biflow
 - (L4) Payload Length (PL)
 - Inter-Arrival Time (IAT)
 - Direction (**DIR**):
upstream/downstream
 - TCP Rcv Window (**WIN**):
0 for UDP packets



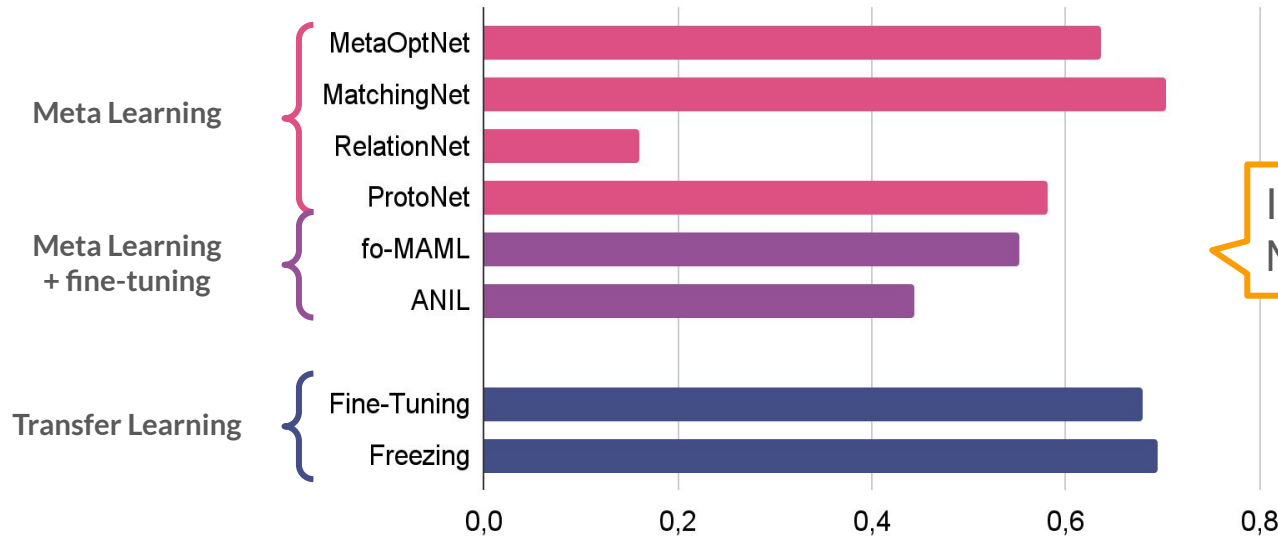
Experimenting with FSL: Embedding Function



FSL approaches for Mobile-app Encrypted TC

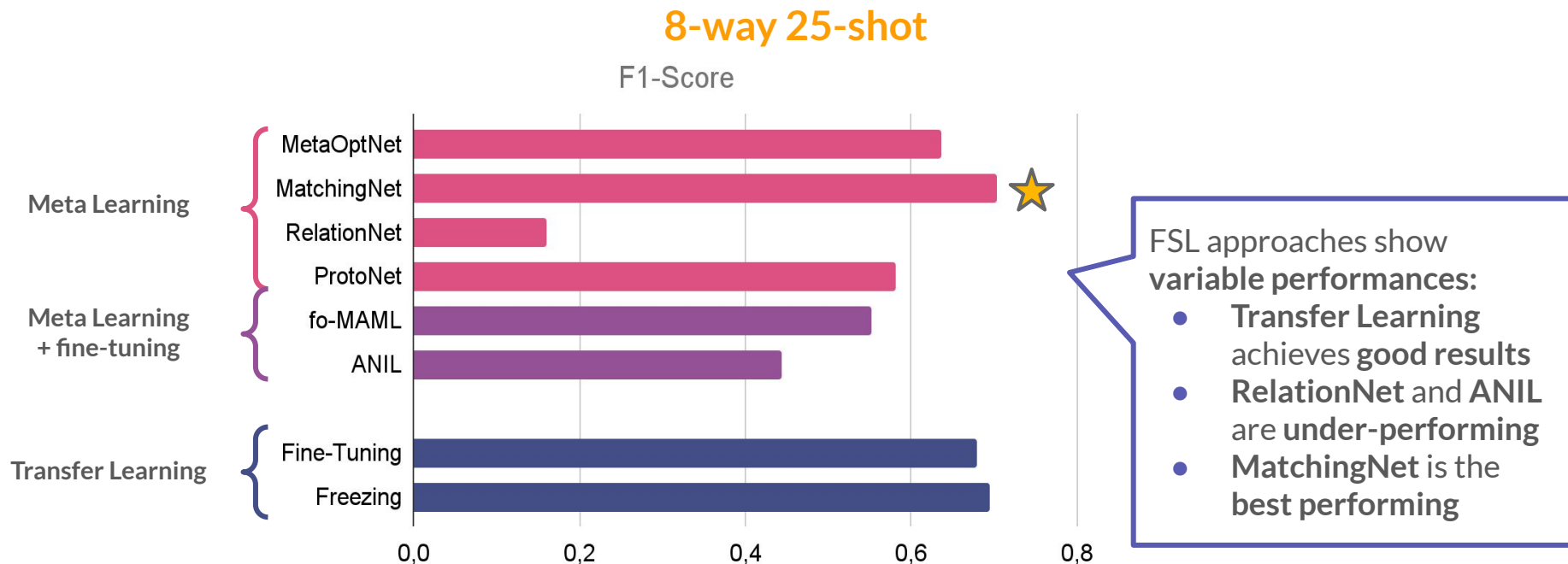
8-way 25-shot

F1-Score



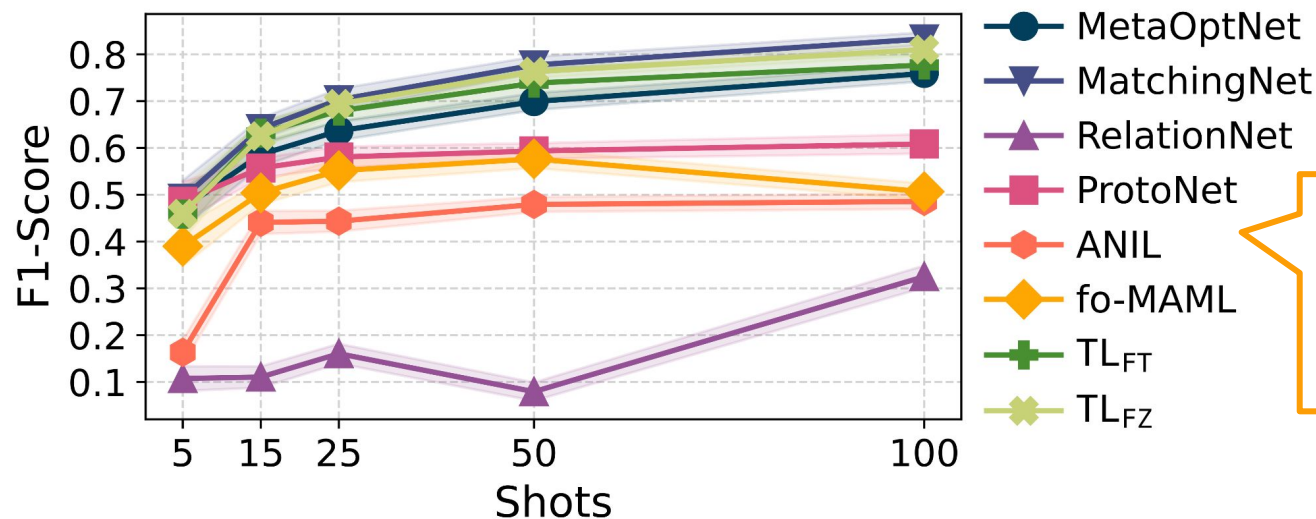
Is FSL applicable to Mobile-app Encrypted TC?

FSL approaches for Mobile-app Encrypted TC



Impact of the number of Biflows

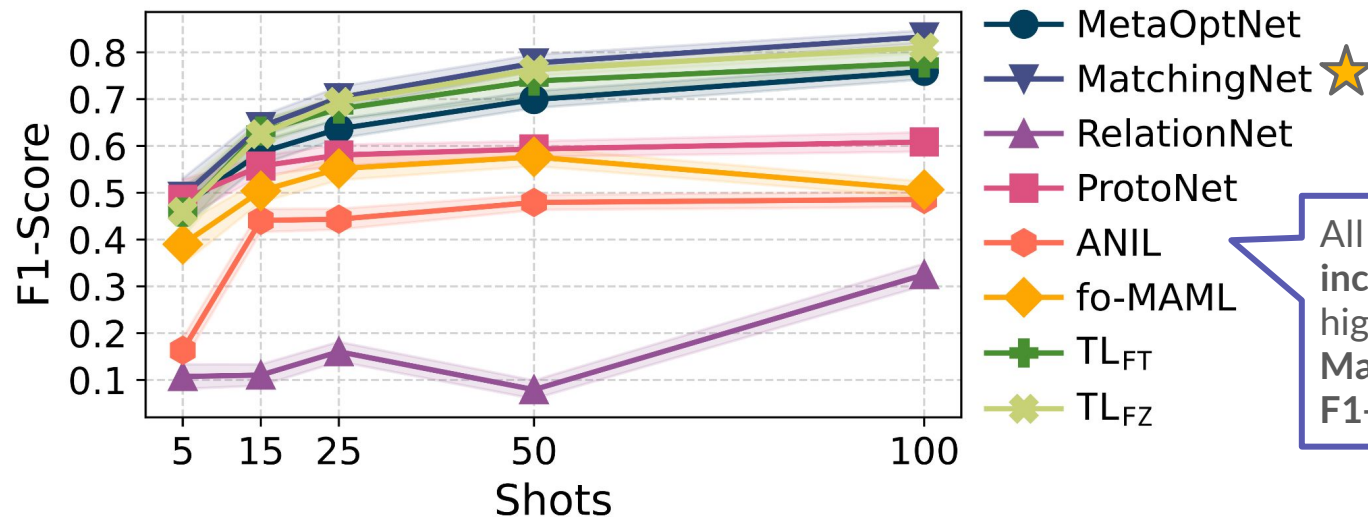
8-way K-shot



How many biflows (shots) per App we need for classify the rare Apps?

Impact of the number of Biflows

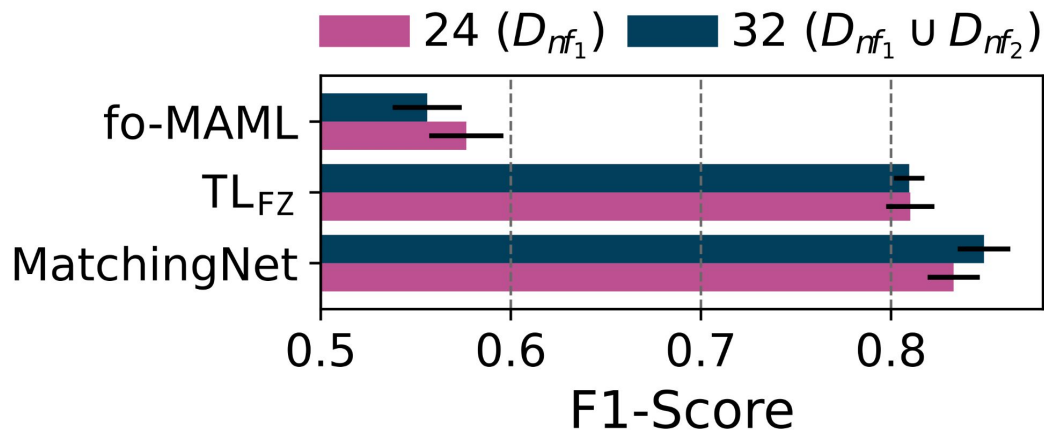
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All FSL approaches significantly increase their F1-score for higher shots.
MatchingNet achieves an F1-score > 80% when $K = 100$

Impact of a wider App pool during training

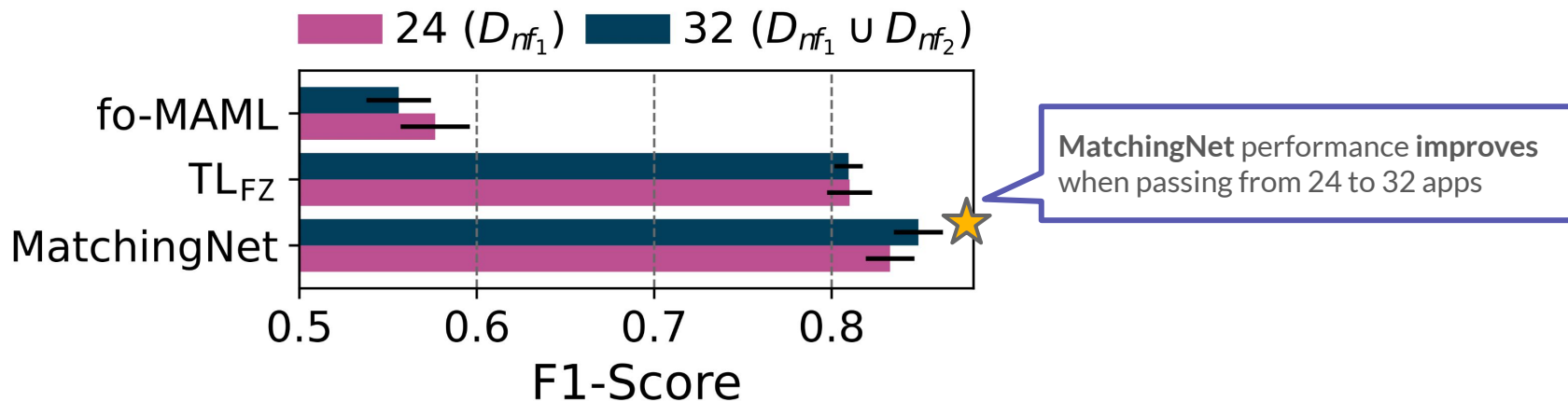
8-way 100-shot



We want to evaluate the ability of the algorithms to extend acquired knowledge on minority classes by using a wider train class pool

Impact of a wider App pool during training

8-way 100-shot



Ongoing and Future Directions

- Optimization of the learning objective by using more complex loss functions to enhance the goodness of embeddings
- The adoption of **different embedding functions** (e.g., **multimodal architectures**) to explore their benefits in this context
- The investigation of **data-based approaches** with the augmentation of samples from few-shot classes

Thanks for your attention

Questions?



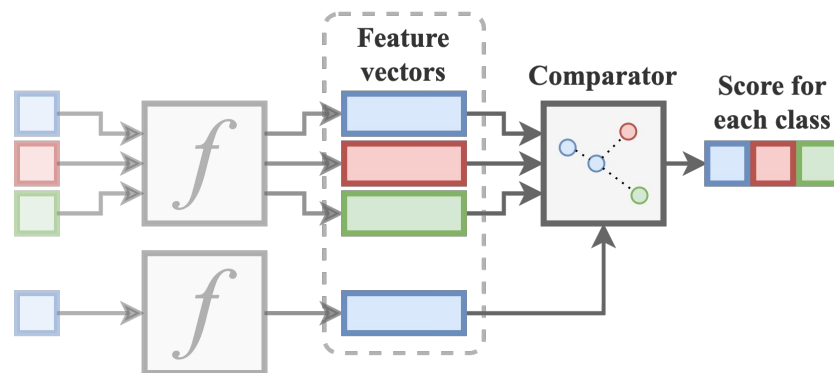
Contacts: giampaolo.bovenzi@unina.it - wpage.unina.it/giampaolo.bovenzi

Backup Slides



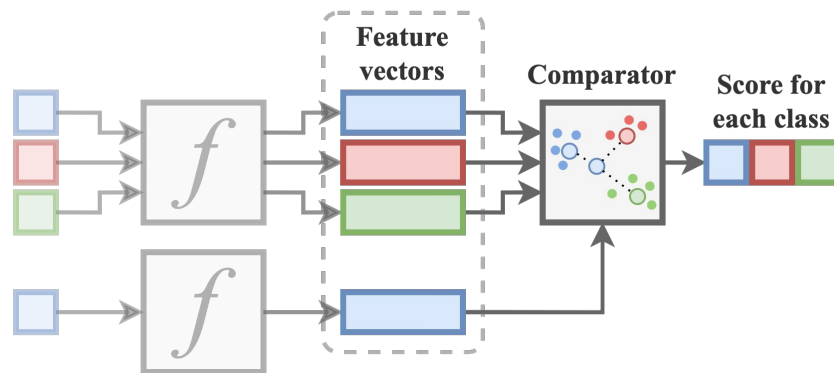
Meta-Learning Approaches

- **Matching Networks**
 - Distance between the query and support set samples in the embedded space (nearest-neighbor based)



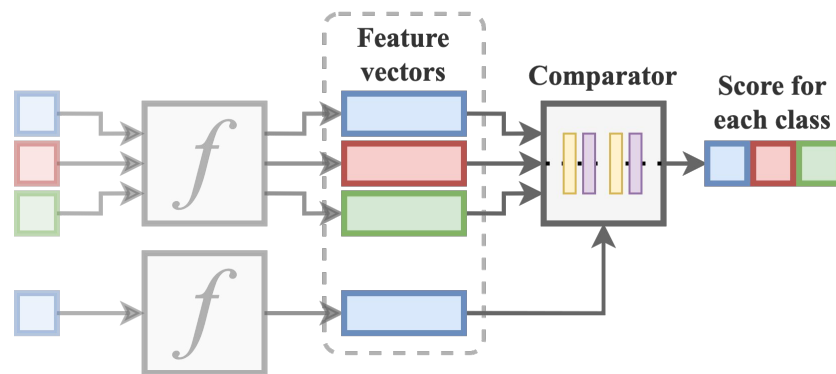
Meta-Learning Approaches

- Matching Networks
- Prototypical Networks
 - Distance between the query sample and *prototypes* of each class in the support set in the embedded space (nearest-neighbor based)



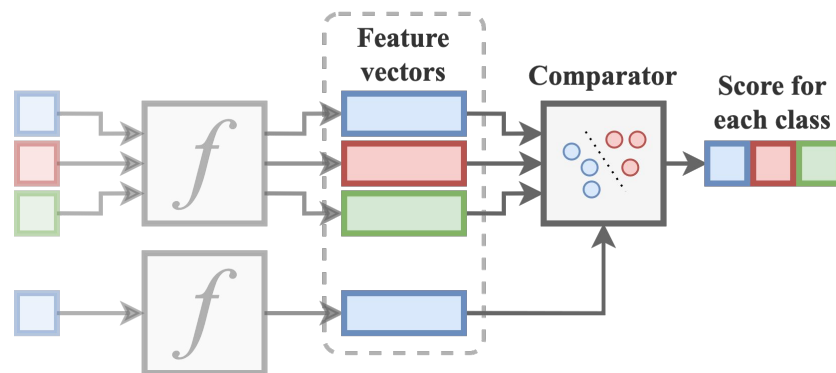
Meta-Learning Approaches

- Matching Networks
- Prototypical Networks
- Relational Networks
 - Measure the similarity in the embedded space between the query sample and prototypes of each class in the support set through a **CNN** with a **Sigmoid Function**



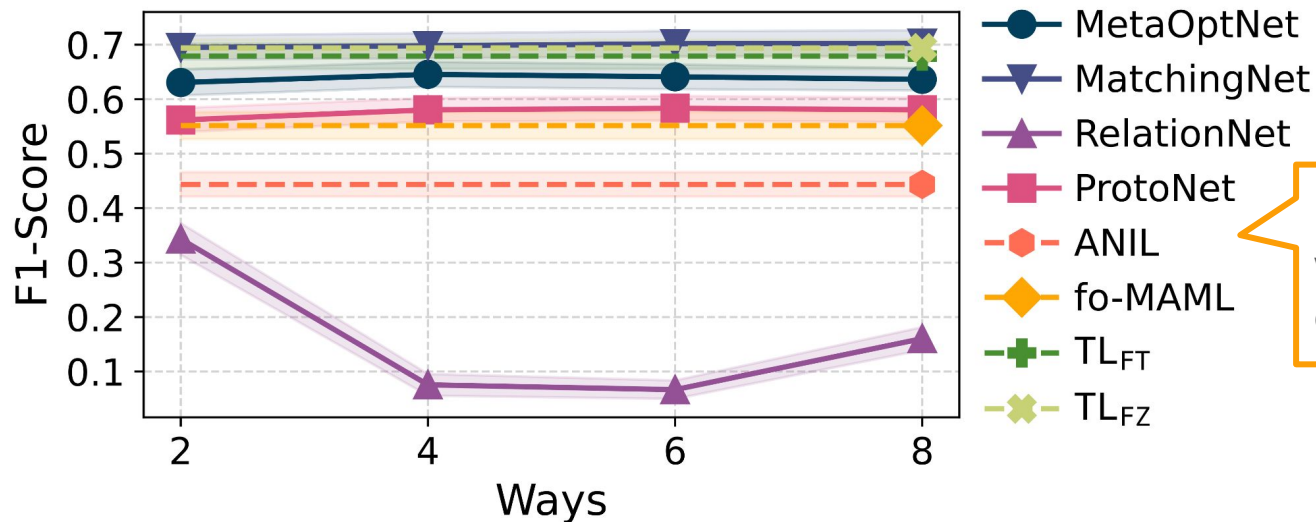
Meta-Learning Approaches

- Matching Networks
- Prototypical Networks
- Relational Networks
- MetaOptNet
 - Employs a linear **Support Vector Machine (SVM)** as a base learner



Impact of the number of Apps

N-way 25-shot



How many Apps (ways) we need to be able to classify rare Apps?

Impact of the number of Apps

N-way 25-shot

