Oral Presentation in LABELS Workshop at MICCAI 2018, Granada, Spain

Capsule Networks against Medical Imaging Data Challenges

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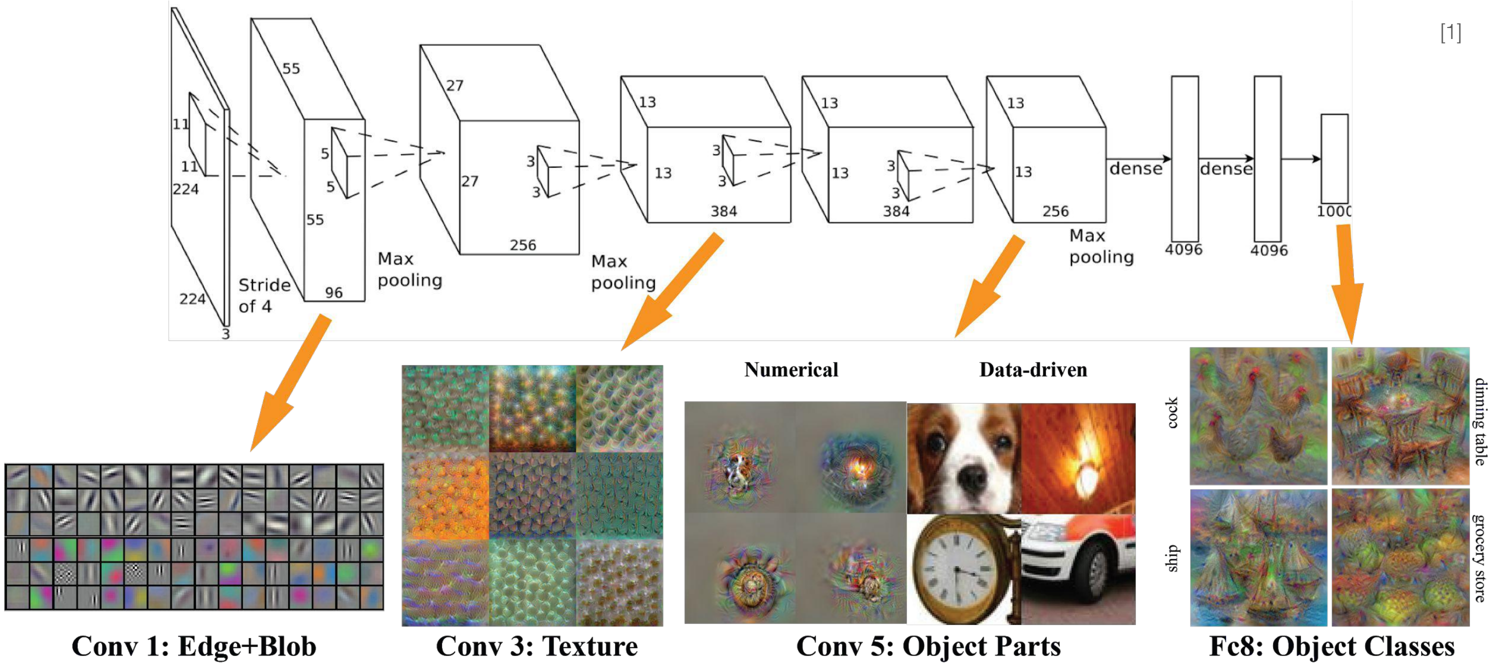
Technische Universität München

Diana Mateus
École Centrale de Nantes

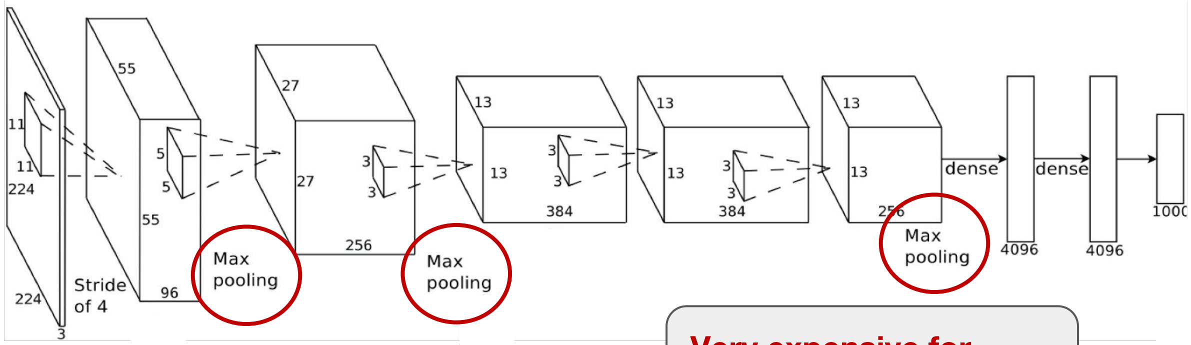
CONVOLUTIONAL NETWORKS: FEATURE EXTRACTION

[1]



[1] http://vision03.csail.mit.edu/cnn_art/index.html

CONVOLUTIONAL NETWORKS: SHORTCOMINGS



[1]

- ConvNets are **not spatial invariant**, need to include: scale, rotations, translations

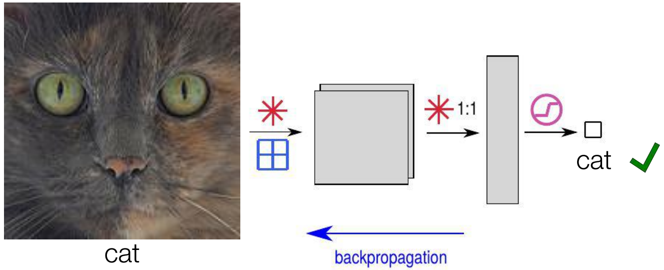
Very expensive for medical images ⚠

[2]

[1] http://vision03.csail.mit.edu/cnn_art/index.html [2] https://www.flickr.com/ #cat

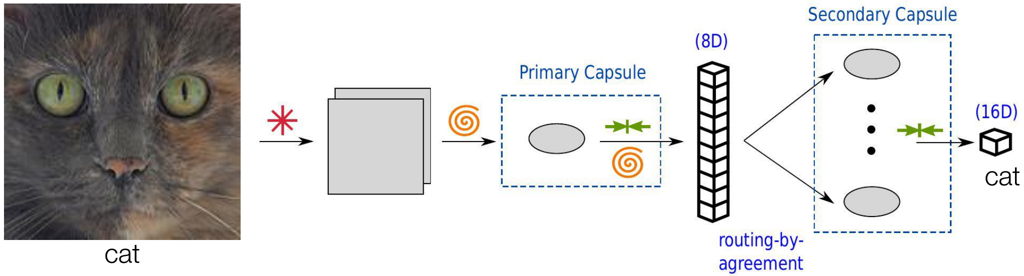
CONVOLUTIONAL *vs.* CAPSULE NETWORK

ConvNet



presence / absence

CapsNet



Convolution   1:1 Fully-connected   Pooling   Softmax   Reshape   Squash

CONVOLUTIONAL *vs.* CAPSULE NETWORK

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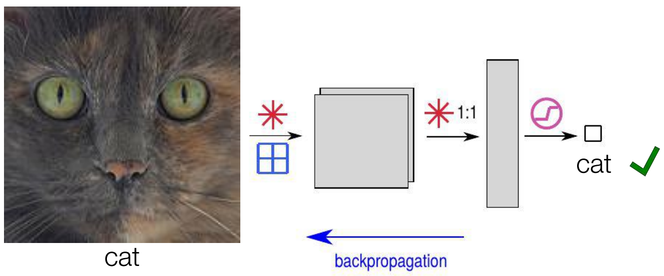

presence / absence

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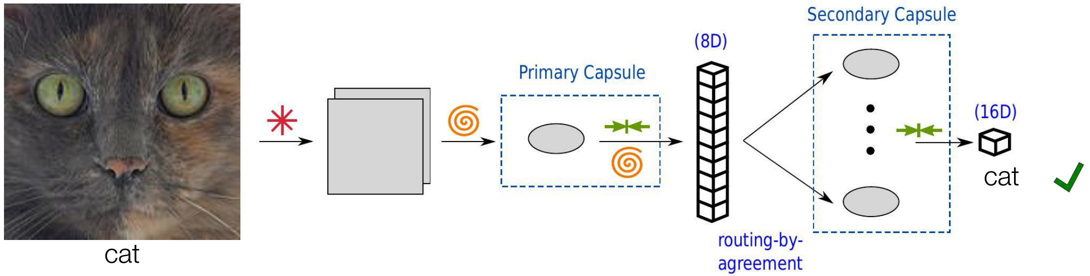
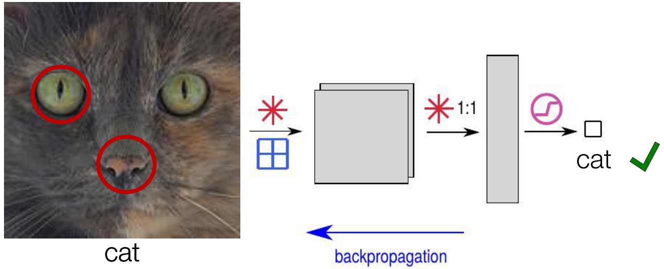


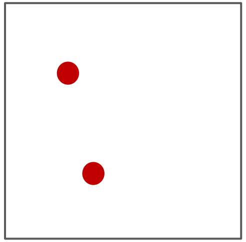
presence / absence (length of the vector)

+ pose: e.g. spatial location, scale, rotation, etc

CONVOLUTIONAL *vs.* CAPSULE NETWORK

ConvNet





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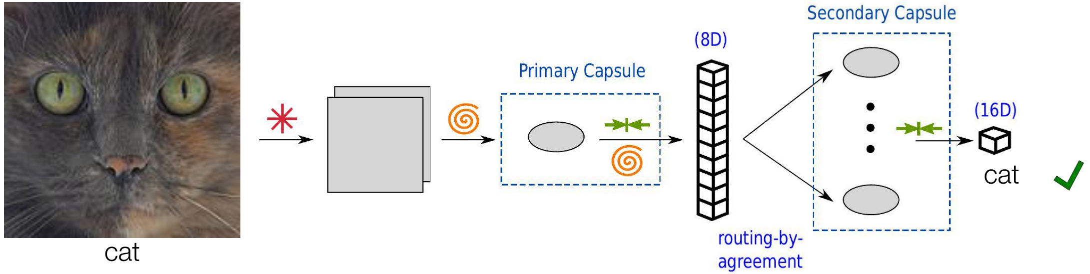

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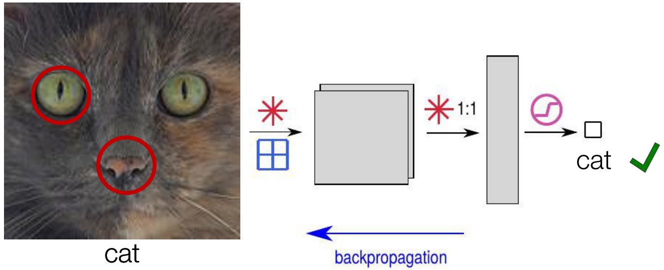

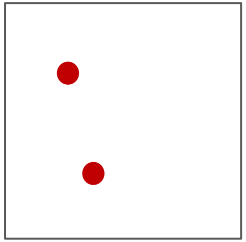

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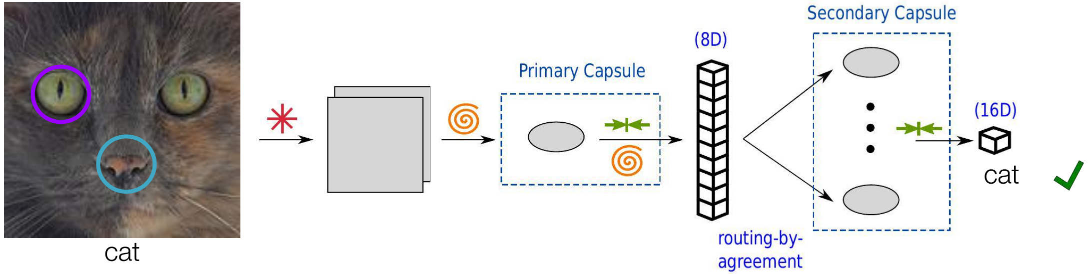

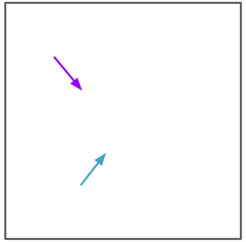

CONVOLUTIONAL *vs.* CAPSULE NETWORK

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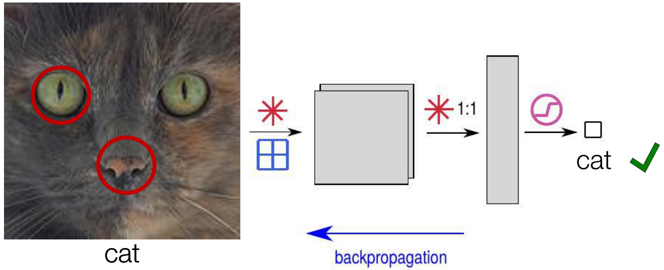

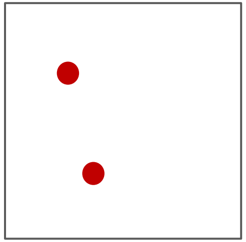

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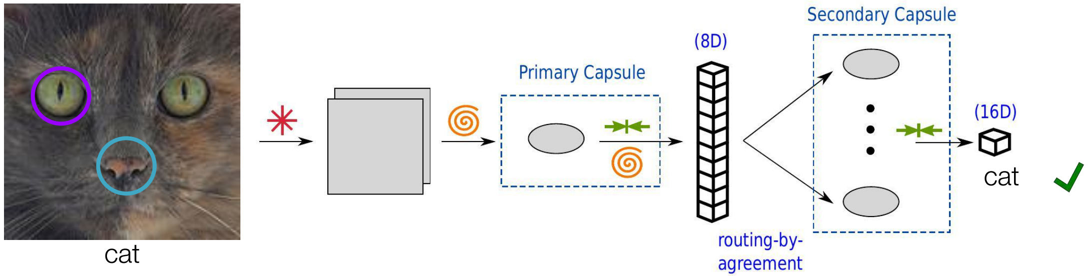
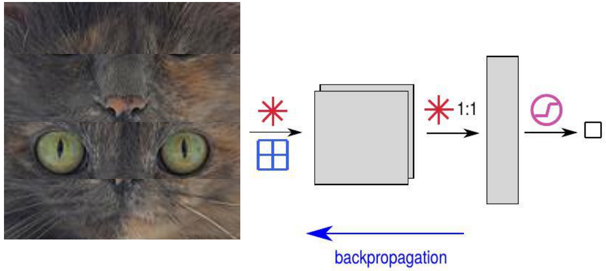


strong agreement

CONVOLUTIONAL *vs.* CAPSULE NETWORK

ConvNet



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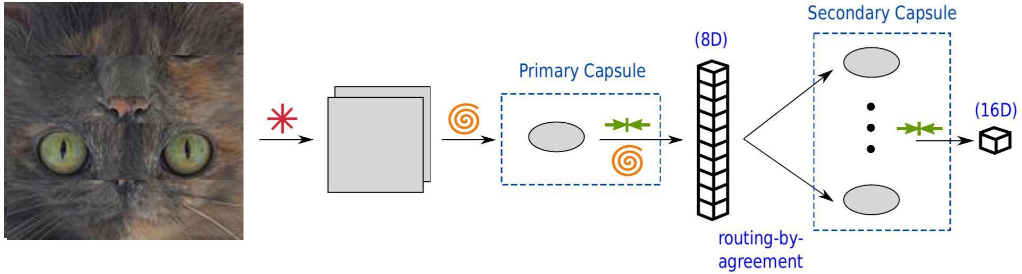

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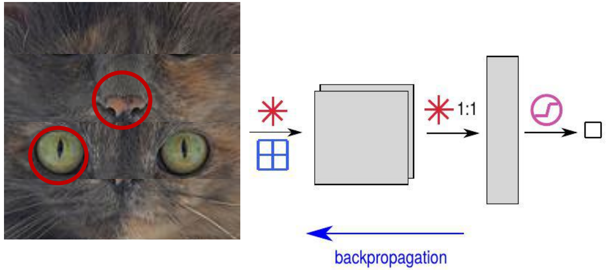

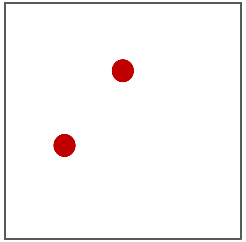

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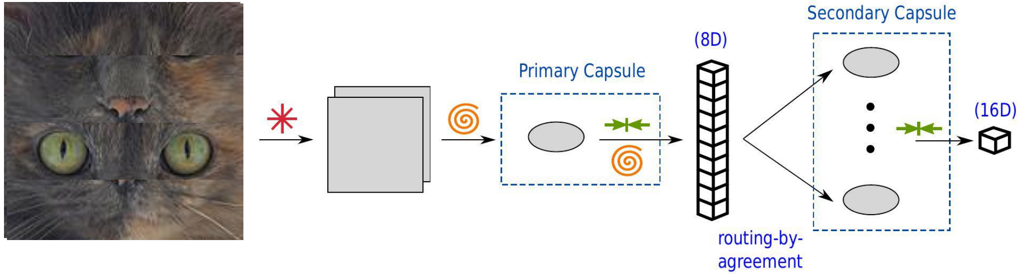

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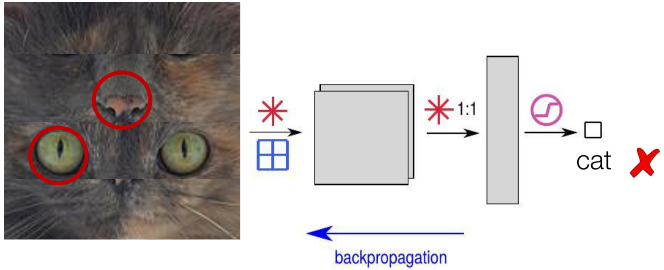
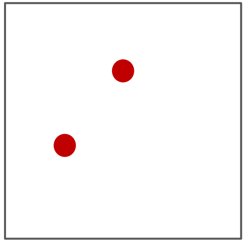


detect **"object" parts** (features) are present



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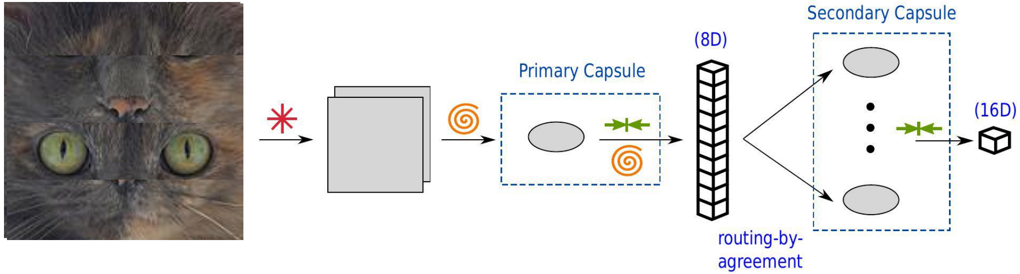

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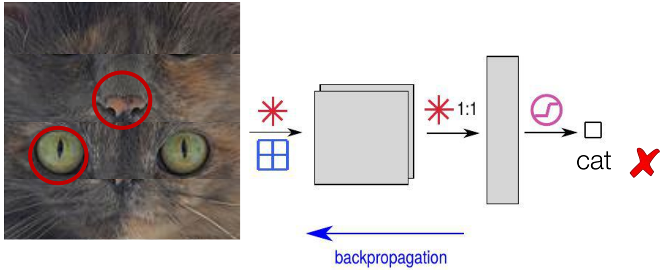

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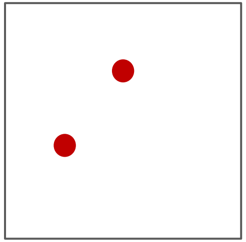

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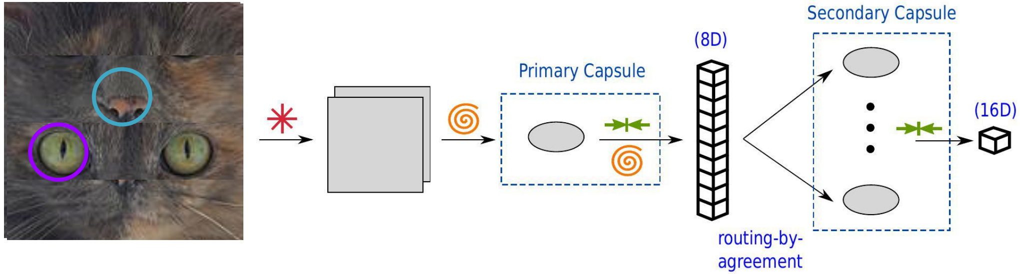

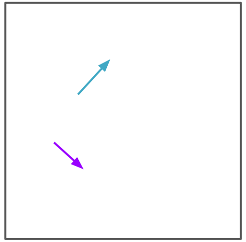

CONVOLUTIONAL *vs.* CAPSULE NETWORK

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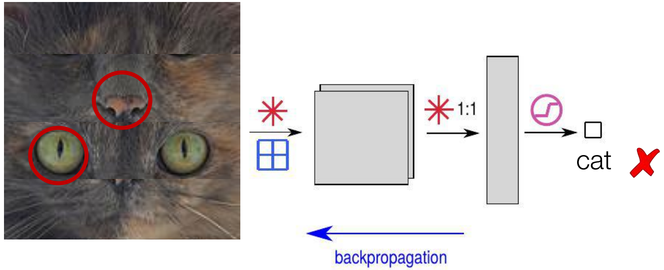

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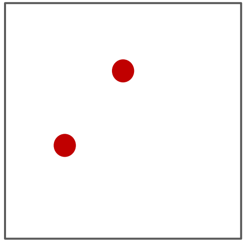

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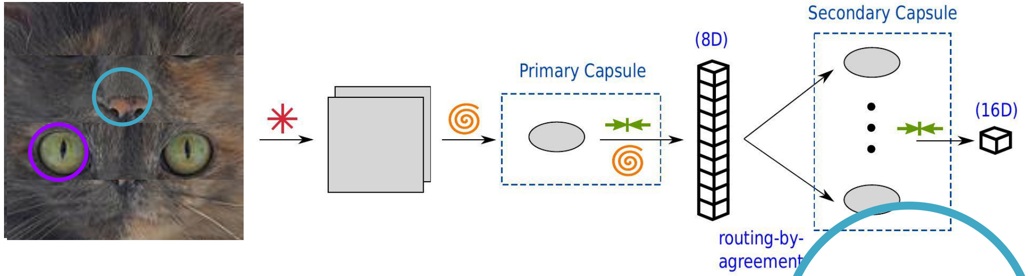

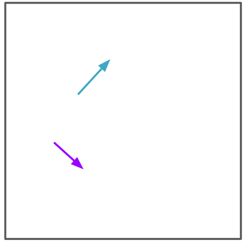

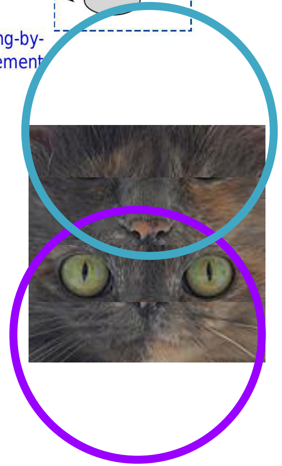

not agreement

CONVOLUTIONAL *vs.* CAPSULE NETWORK

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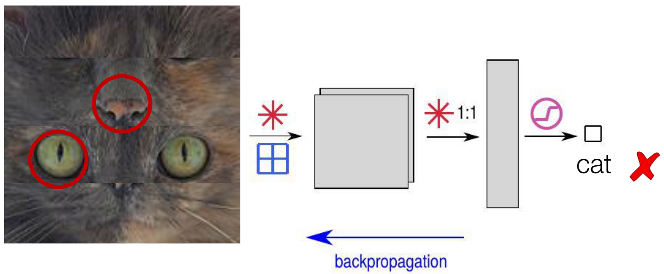

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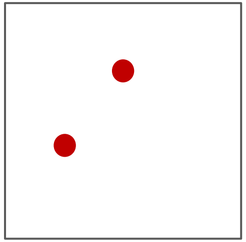

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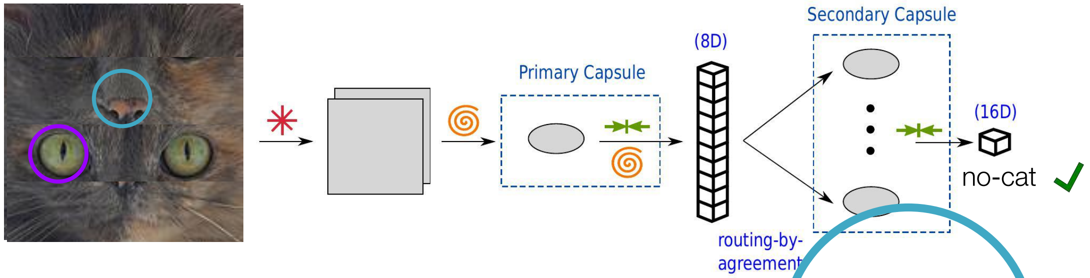

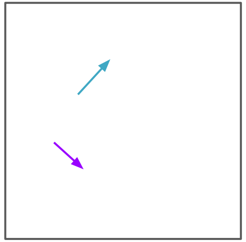

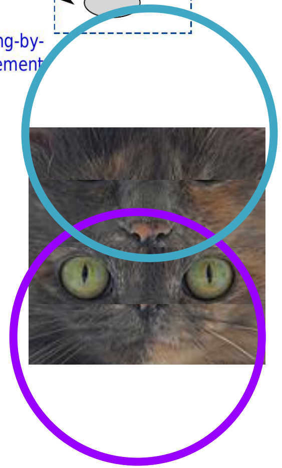

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CONVOLUTIONAL *vs.* CAPSULE NETWORK

Summary of differences:

	ConvNets	**CapsNets**
Layer	pooling	---
Process	scalar	vector
Optimization	backpropagation	routing-by-agreement
Loss	cross-entropy	margin + reconstruction

CONVOLUTIONAL *vs.* CAPSULE NETWORK

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	ConvNets	**CapsNets**
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Loss	cross-entropy	margin + reconstruction

Margin loss: $||v_k|| > 0.9$ -> instance is present
$||v_k|| < 0.1$ -> instance is absent

HYPOTHESIS

CapsNets are designed to **learn** the **pose** of the instance along its **presence**. Consequently, less variations of the instance (**fewer** annotated images) are needed.

Medical datasets are often **small** and **highly imbalanced**.

HYPOTHESIS

We argue that CapsNet will perform better than ConvNets under medical data challenges.

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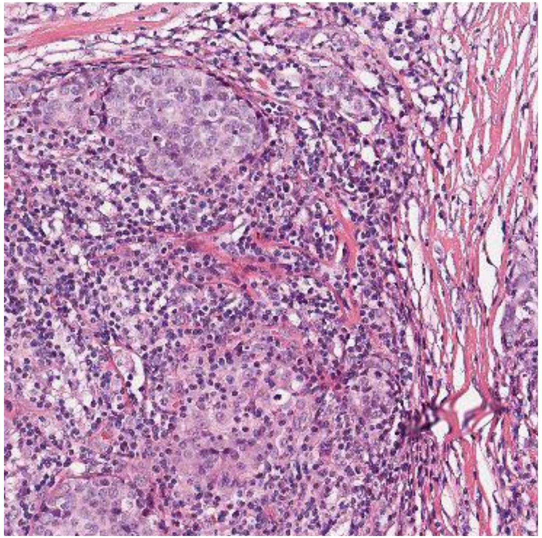
(1) How do networks behave under decreasing **amounts of training data**?

(2) Is there a change in their response to **class-imbalance**?

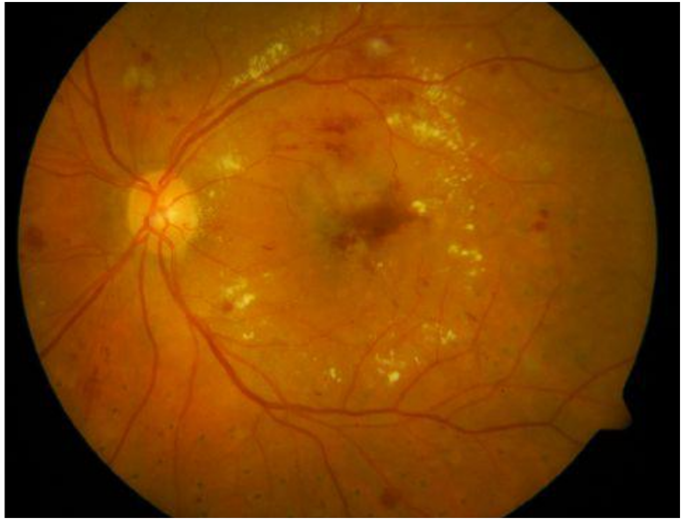
(3) Is there any benefit from **data augmentation** as a complementary strategy?

DATASETS

i) Mitosis detection (TUPAC16) [1]



ii) Diabetic retinopathy detection (DIARETDB1) [2]



[1] Tumor Proliferation Assessment Challenge 2016
(TUPAC16 http://tupac.tue-image.nl/)

[2] Standard Diabetic Retinopathy Database - Calibration level 1
(DIARETDB1 http://www.it.lut.fi/project/imageret/diaretdb1/)

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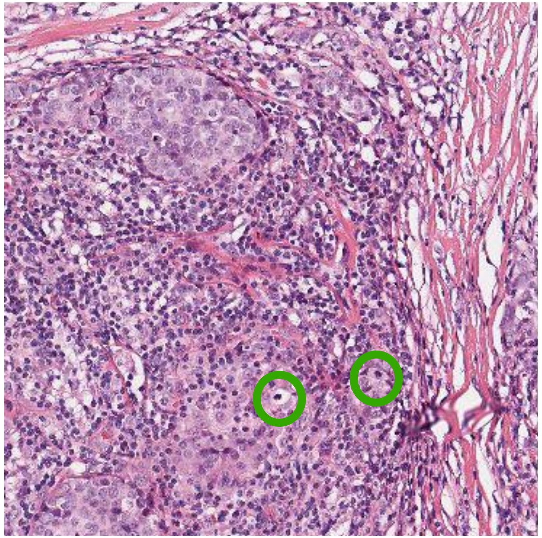

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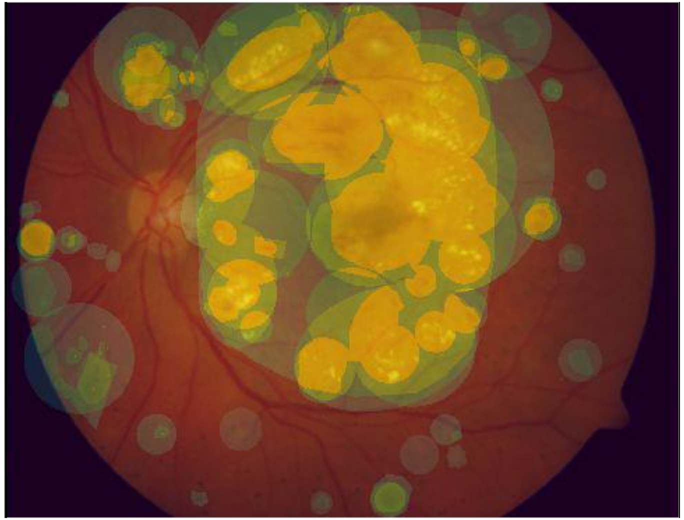

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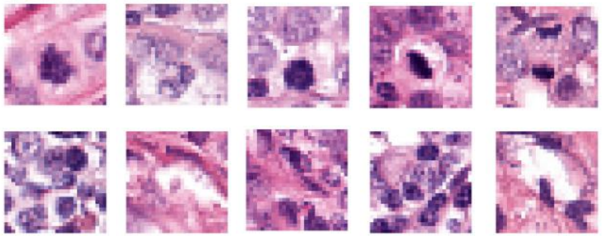

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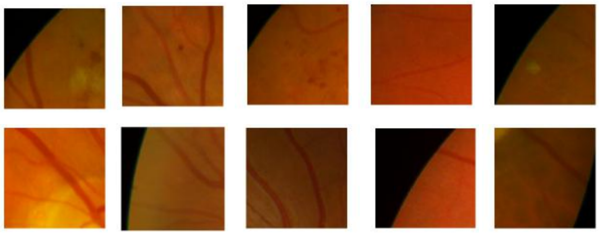
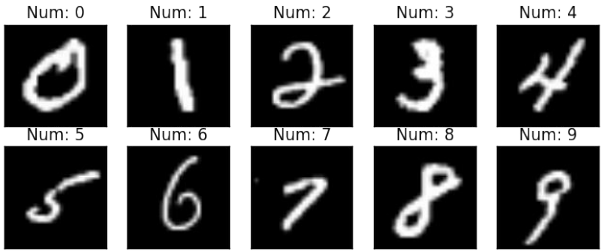
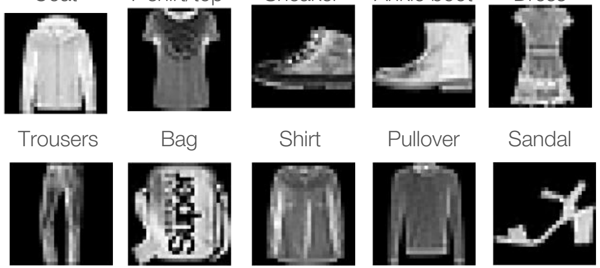


iii) Handwritten Digit Recognition (MNIST) [1]



[1] MNIST database of handwritten digits
(MNIST http://yann.lecun.com/exdb/mnist/)

iv) Clothes Classification (Fashion-MNIST) [2]

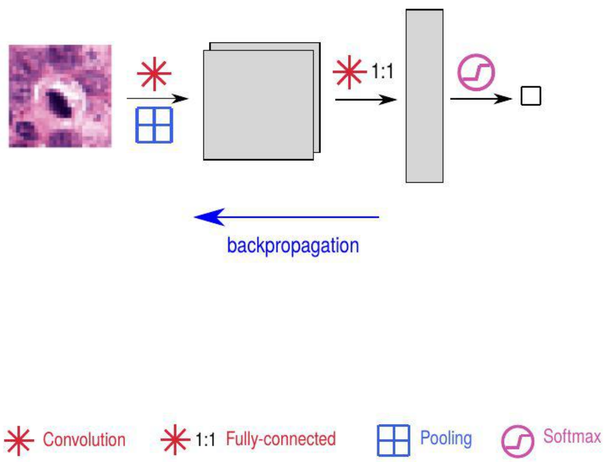


[2] Zalando's article images dataset (Fashion-MNIST
https://github.com/zalandoresearch/fashion-mnist)

ARCHITECTURES

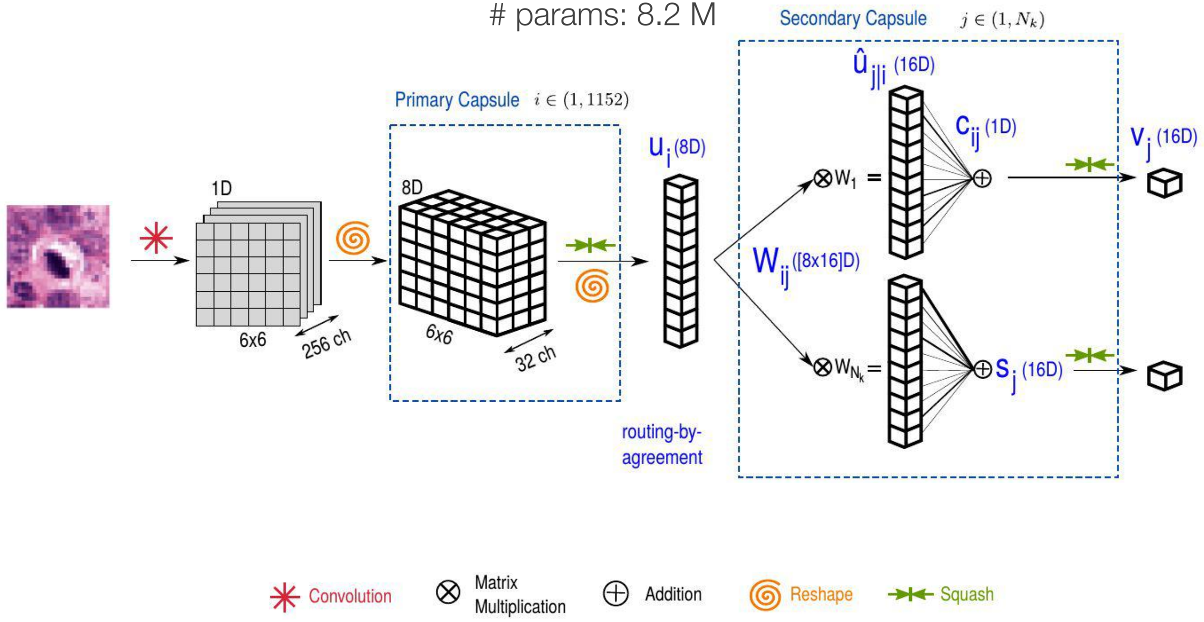
ConvNets (LeNet, Baseline)

params: 60 K, 35.4 M



CapsNet

params: 8.2 M



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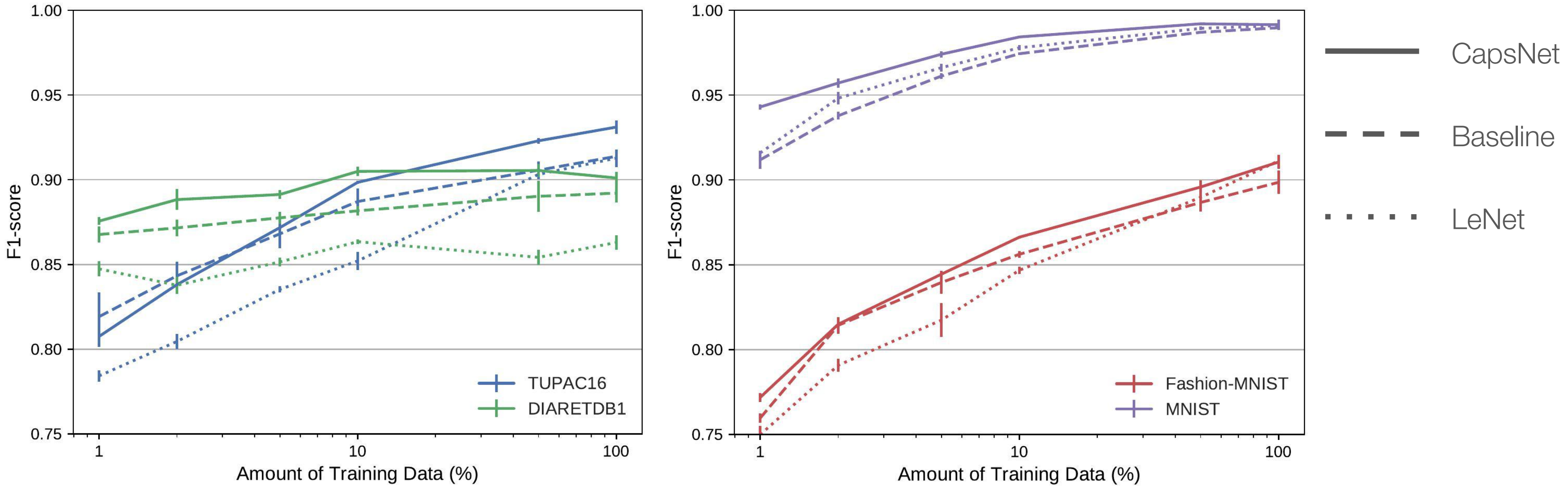

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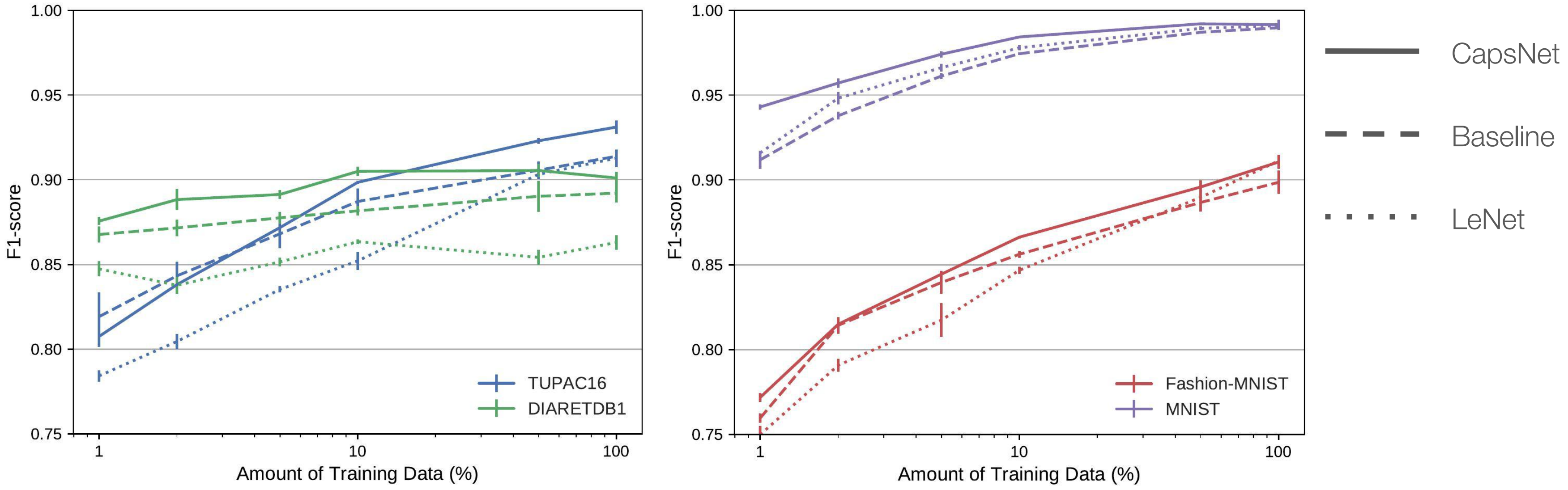

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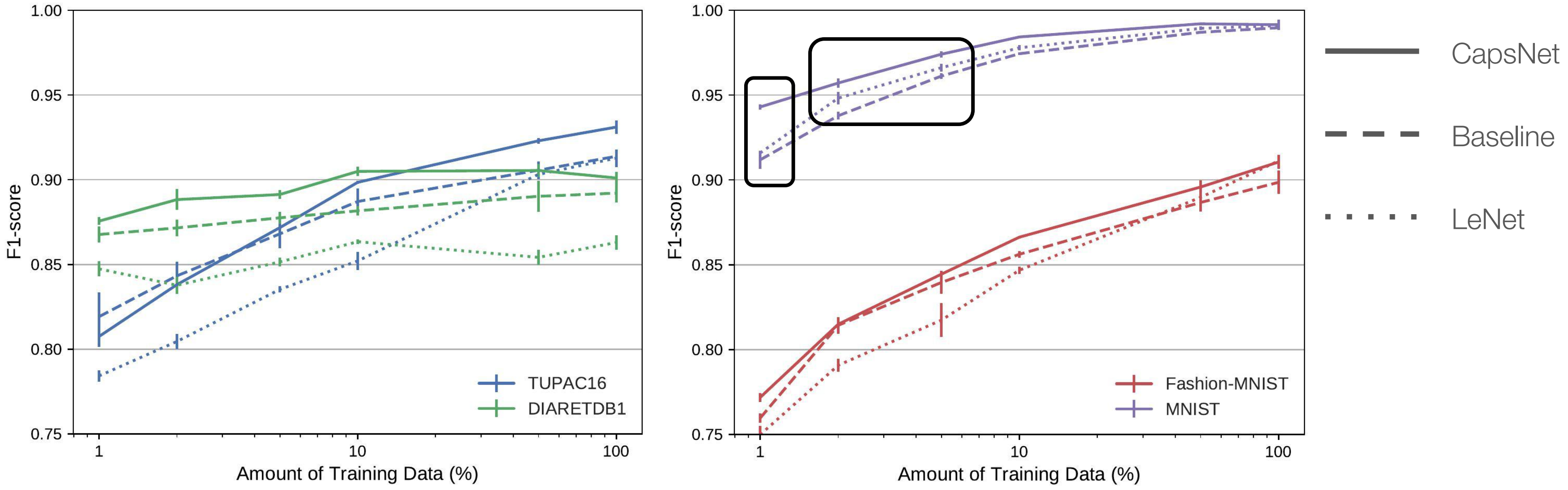

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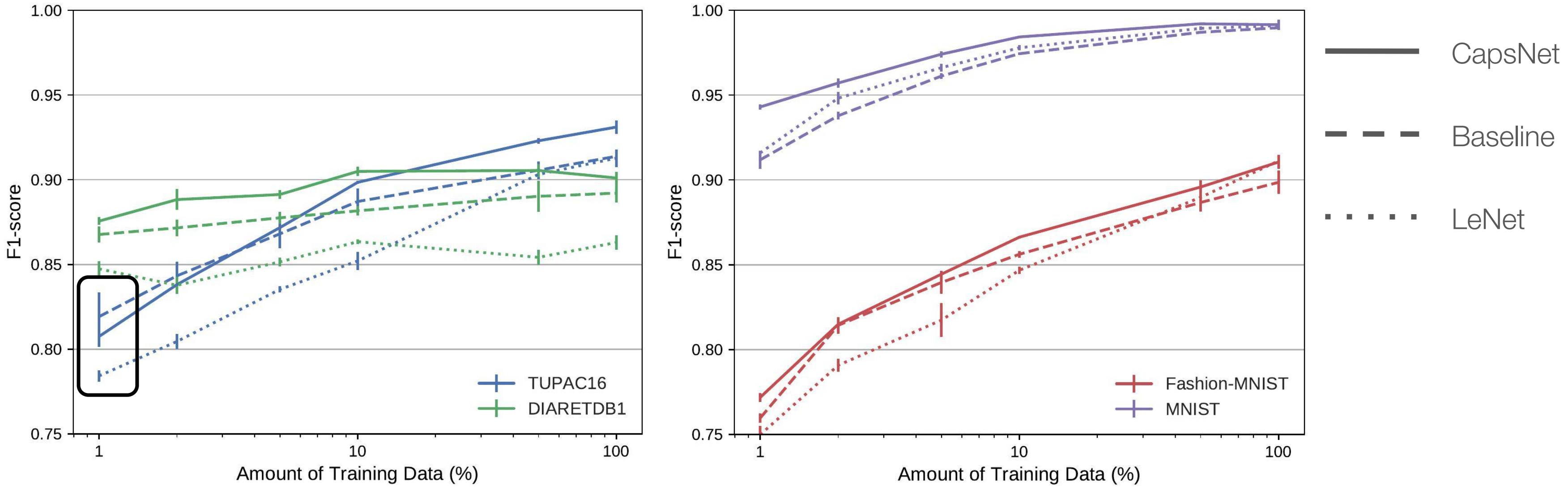

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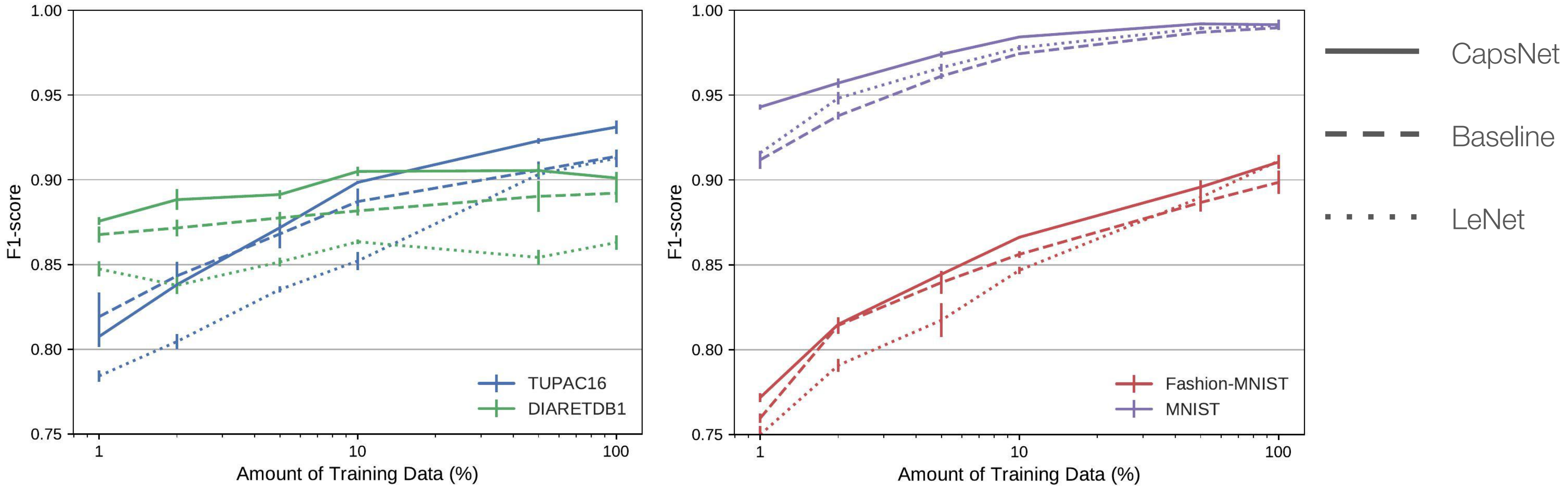

- CapsNet performs overall better than ConvNets (LeNet & Baseline).
- The gap is higher for small amount of data (MNIST).
- Improvement is <u>limited</u> in more complex dataset (TUPAC16).
- All our experiments validated the significance test with a p-value < 0.05 (except for TUPAC16).

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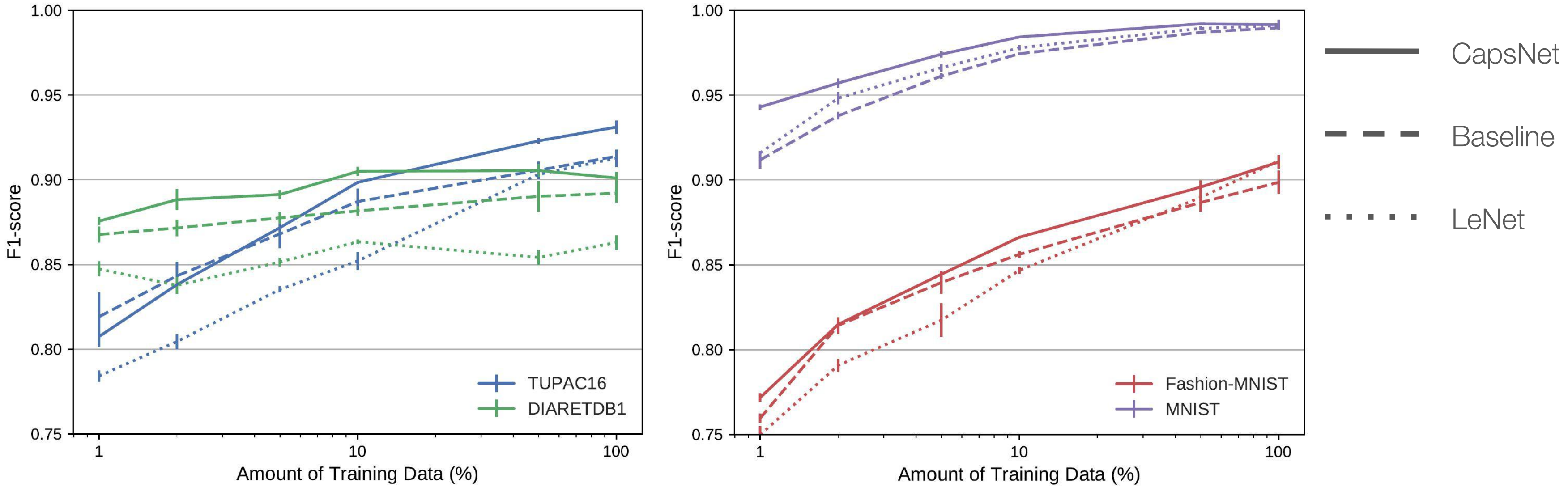

<u>Take home messages</u>:

- CapsNet requires **less images** for a better performance.
- Behaviour can change for different datasets.

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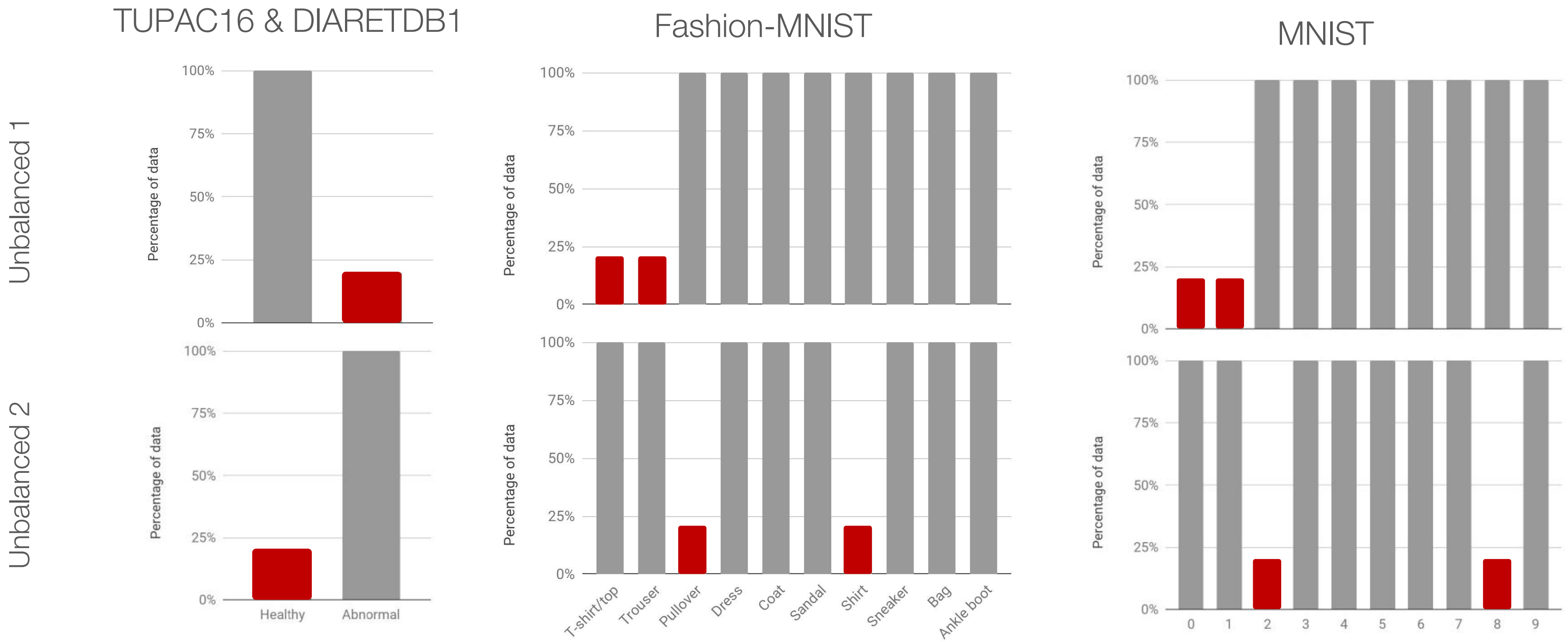

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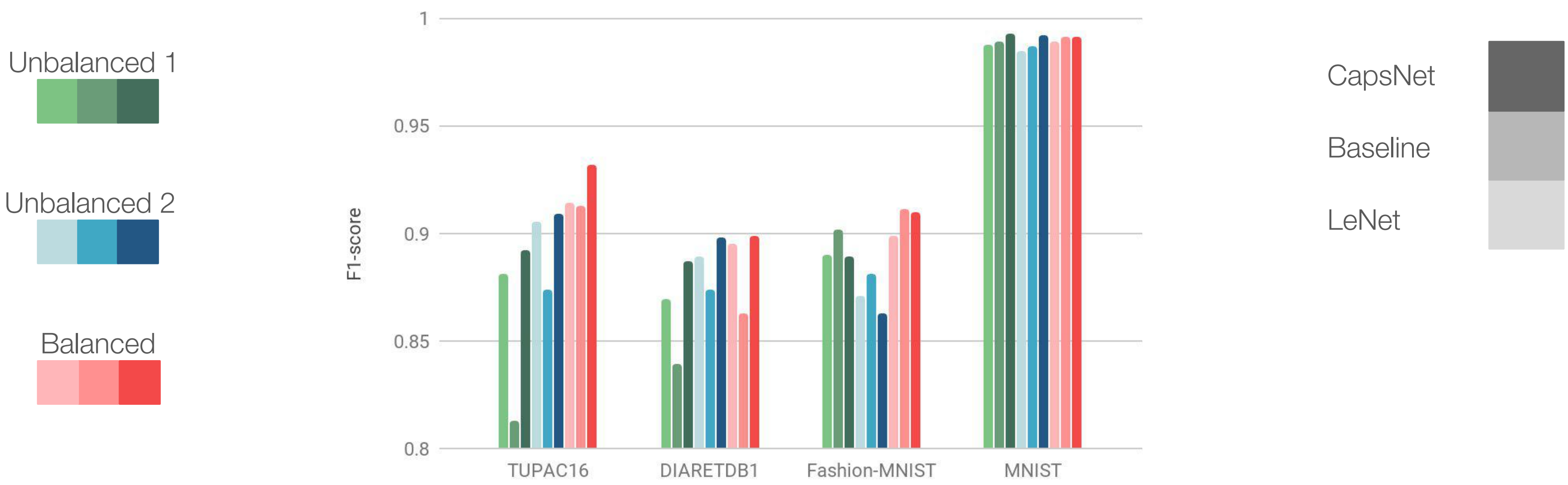

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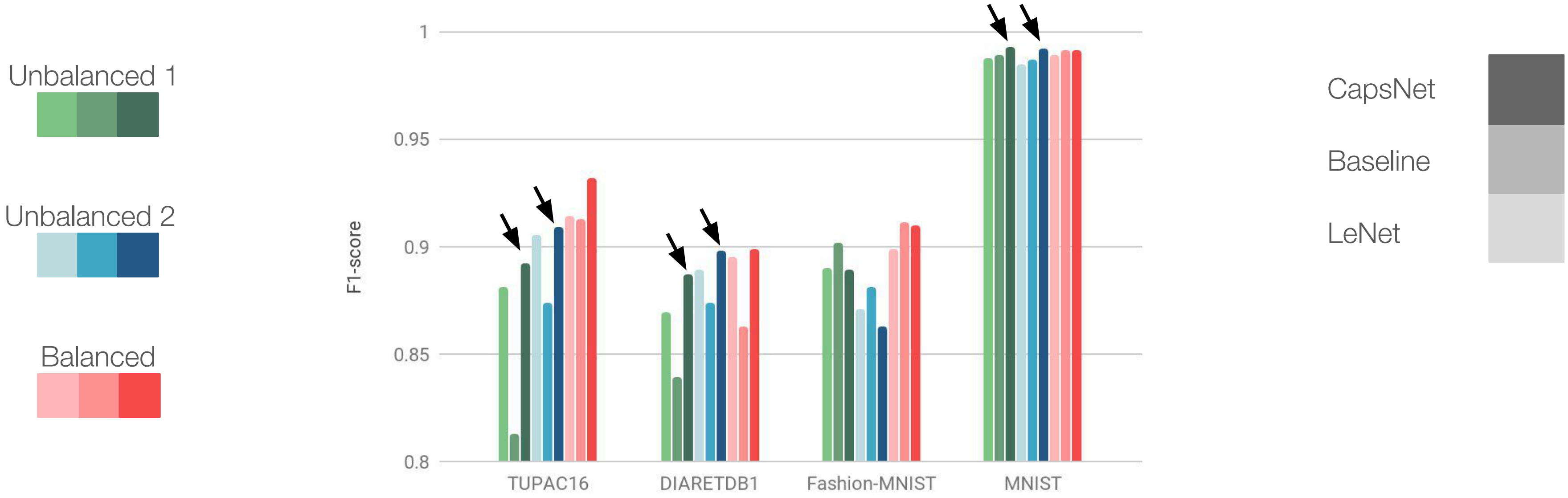

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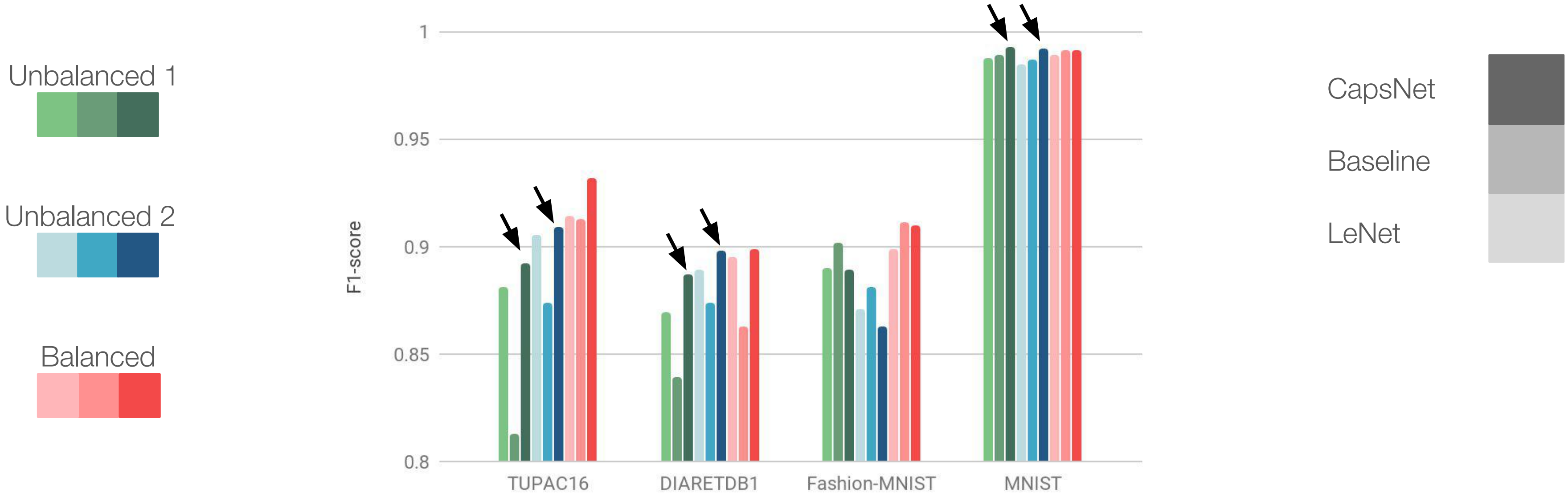

- CapsNet surpasses performance of ConvNets for all cases, except for Fashion-MNIST.
- At least one of the unbalanced cases verified the significance test for all datasets.

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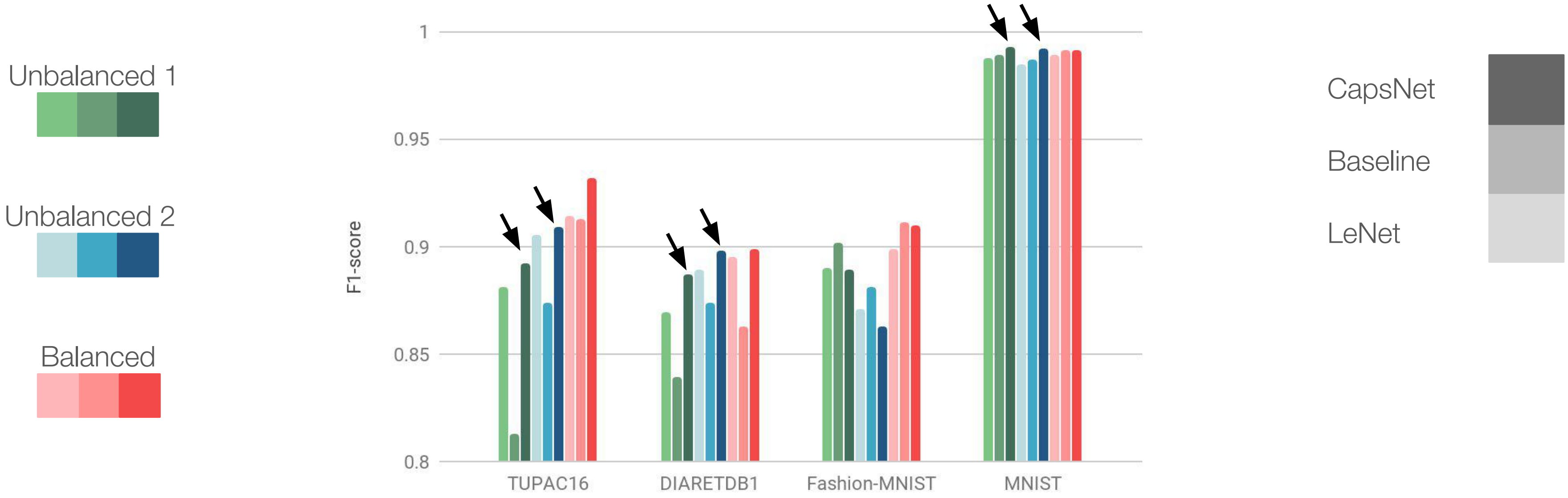

<u>Take home message</u>:

- CapsNet is **more robust** to imbalance in the class distribution.

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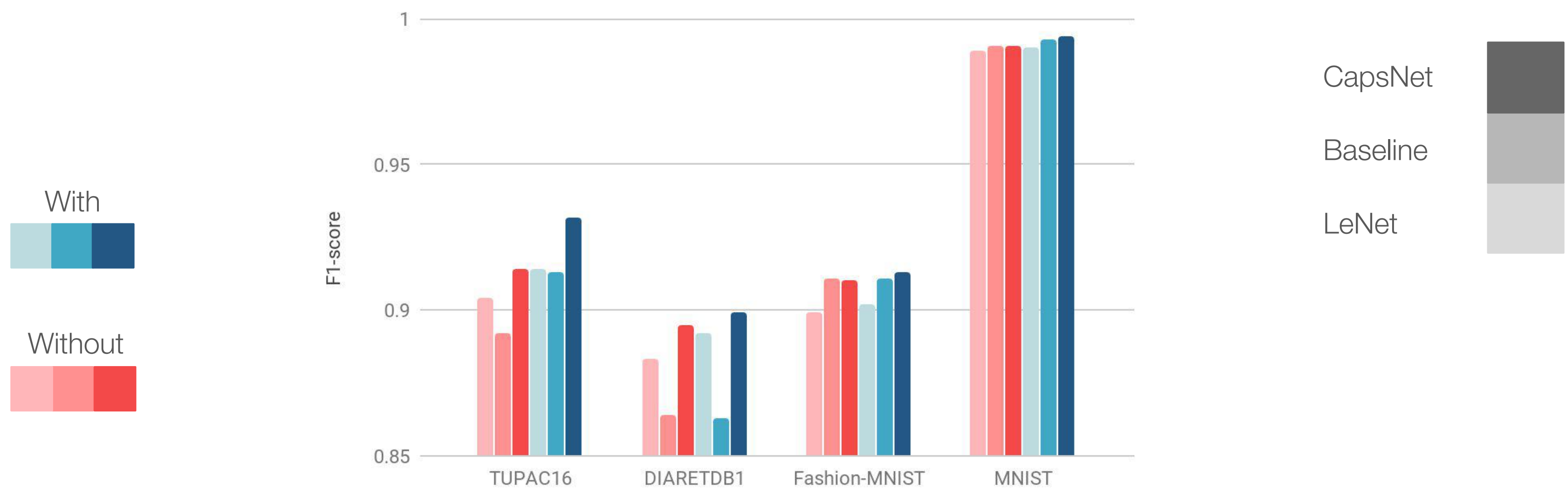

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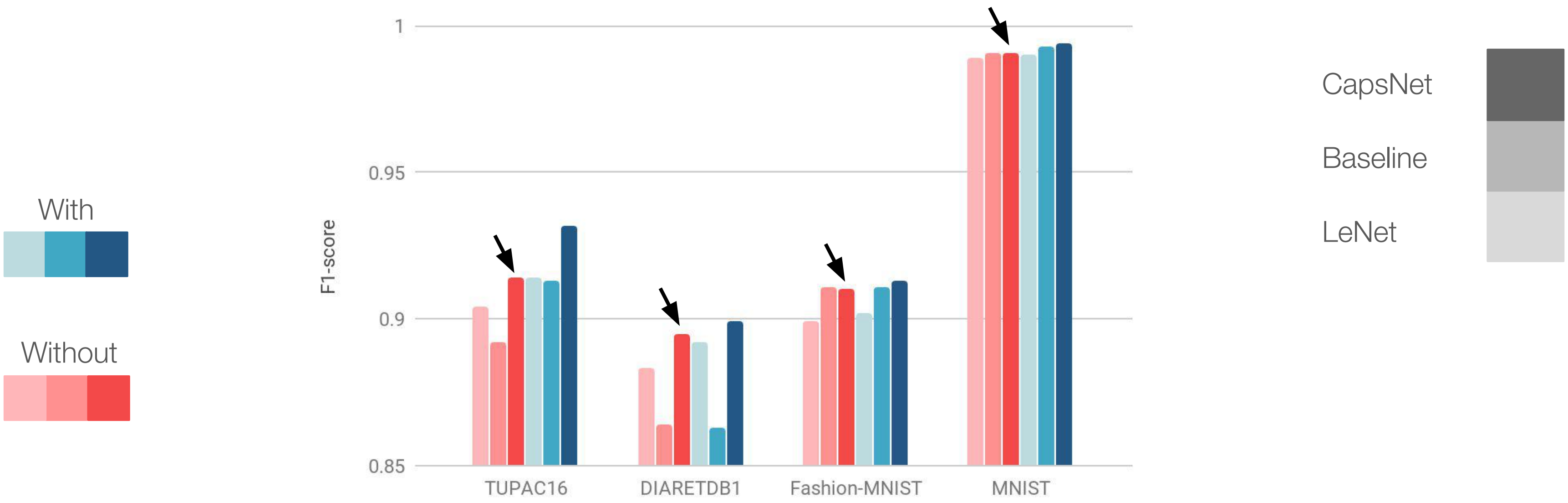

- CapsNet without data augmentation performs … than ConvNets using data augmentation.
  - similarly (TUPAC16, MNIST, Fashion)
  - better (DIARETDB1)

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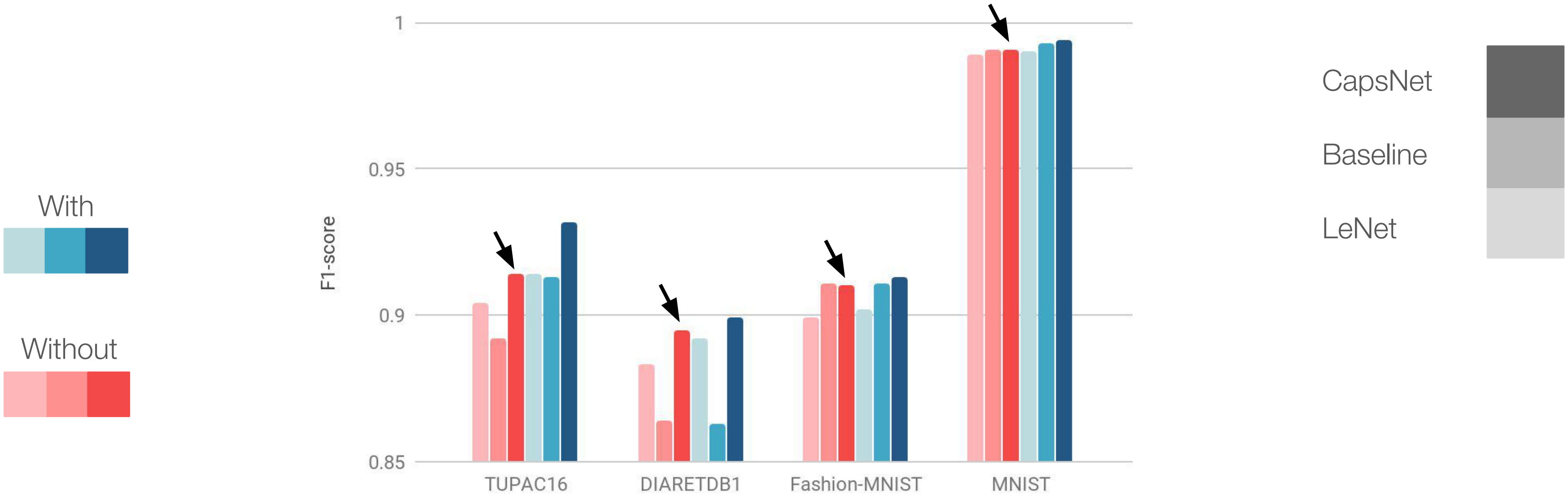
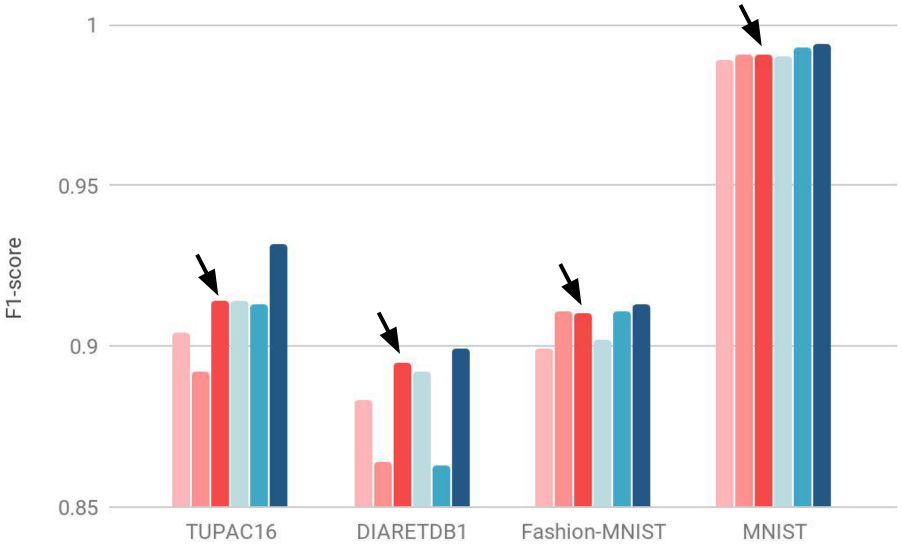


- CapsNet without data augmentation performs … than ConvNets using data augmentation.
  - similarly (TUPAC16, MNIST, Fashion)
  - better (DIARETDB1)
- All results were found significant.

(3) Is there any benefit from **data augmentation** as a complementary strategy?

With

Without



CapsNet

Baseline

LeNet

Take home message:

- CapsNet learns **a stronger representation** with less variability of the data.

Conclusion

+ **Equivariance** modeling, requires to see fewer viewpoints of the instance of interest.

+ Allows to reduce the **number of parameters** for a comparable performance.

+ CapsNet improves CADx classification **performance** under medical data challenges.

- Routing-by-agreement is **slower** than backpropagation (≈ convergence time).

- Improvement is **limited** in more complex datasets (TUPAC16).

- **Reconstructions** are blurry for medical datasets with complex backgrounds.

Outlook

- ➥ Fully convolutional **decoder** to handle complex backgrounds.
- ➥ Explore CapsNets in a **semi-supervised** or **unsupervised** framework.
- ➥ Investigate the latent space to improve **explainability** and **interpretability**.
- ➥ Look into more suitable **medical datasets**, in which neighborhood structure plays a role for diagnosis.

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Thank you for your attention!

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