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Classifyng Objects at Differnts Sizes with Multi-scale Stacked Sequential Learning

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Summary

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1. Problem Motivation
2. Multi-Scale Stacked Sequential Learning
3. Learning at multiple scales
4. Experiments and results
5. Conclusions

Sequential learning

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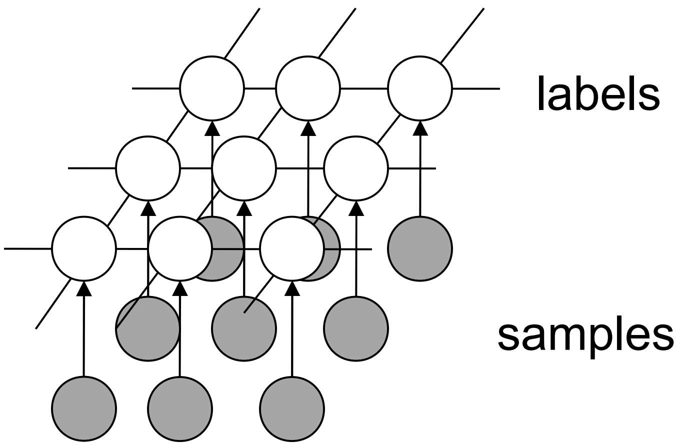
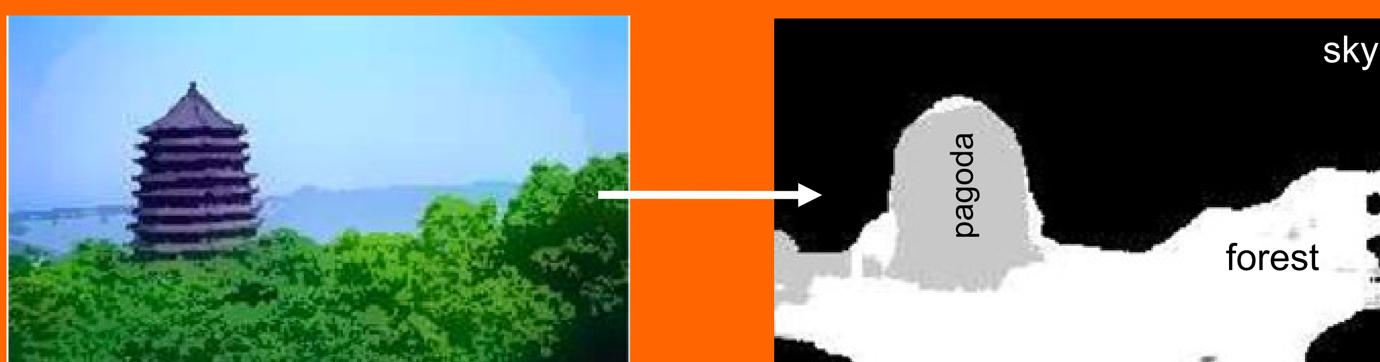


- Classification task.
- Non i.i.d. samples.
- Neighboring samples have some kind of relationship.
- Neighboring labels **also** have some kind of relationship.

1D SL- time/sequence relationship,
2D SL- spatial relationship.

Application: Object Classification

- Access to the full data sequence
- All labels have to be given at a time



Not to be confused with …

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Time series prediction
Real labels up to time t available, only need to predict label at time t+1.

Access to data up to time t.

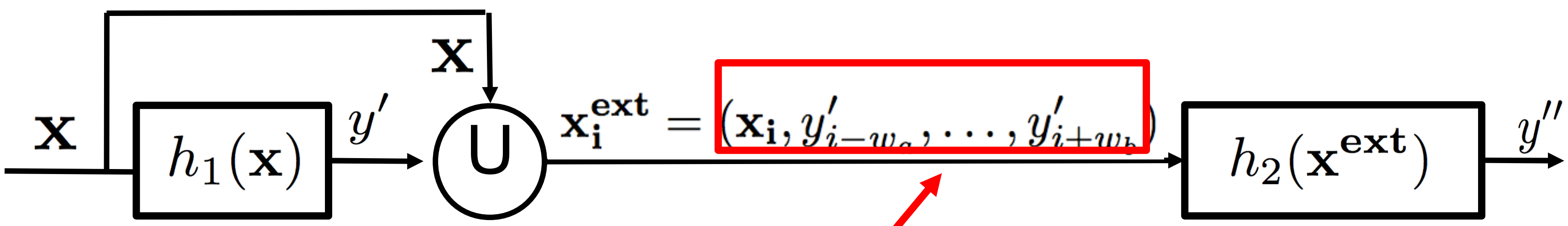
Sequence classification
One label expected from a full sequence

“pagoda”

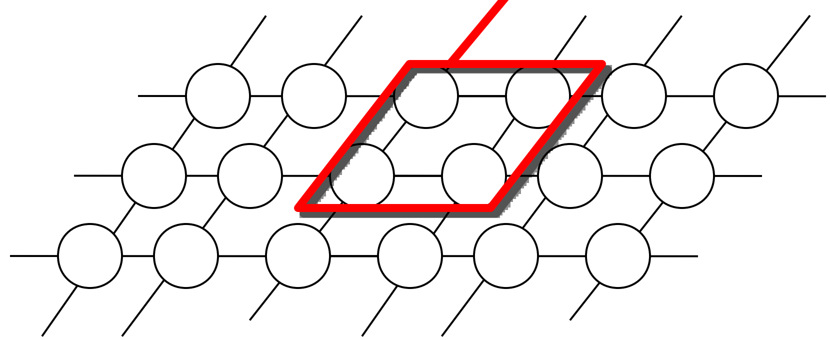
Segmentation
Associated with region division according to some homogeneity criterion

Classifying Objects with SSL

W. Cohen and V. R. de Carvalho, *Stacked sequential learning*, Proc. of IJCAI 2005, pp. 671–676, 2005.



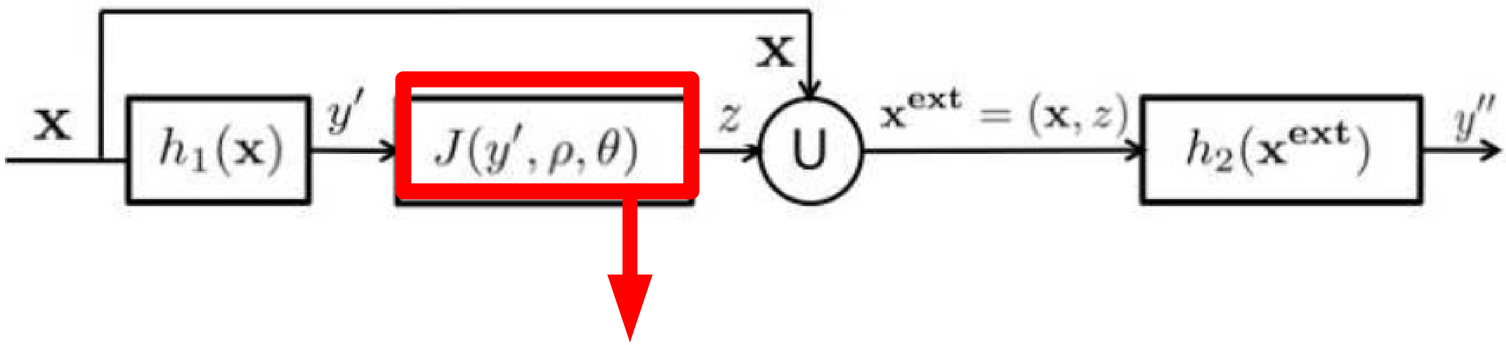
Combination by increasing the input space with data of the neighboring labels



But when classifying objects, each pixel is an example, and quite often relationships between pixels are long-distance relationships inside an object.

Multiscale Stacked Sequential Learning

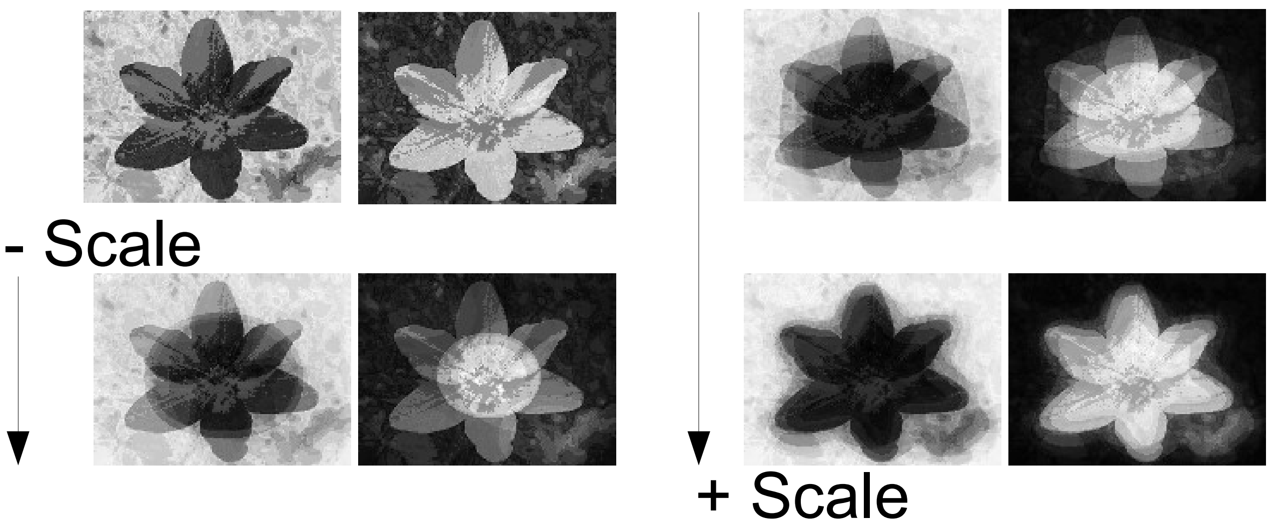
- MSSL: Stacked Sequential Learning that can effectively identify and use long-distance relationships.



- Multiscale decomposition of y' for each label using Gaussian Filters.
- Use of likelihods instead of label value.

Multiscale Stacked Sequential Learning

Background/Flower



- Multiscale decomposition of y' for each label using Gaussian Filters.
- Use of likelihods instead of label value.

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Classifyng Objects

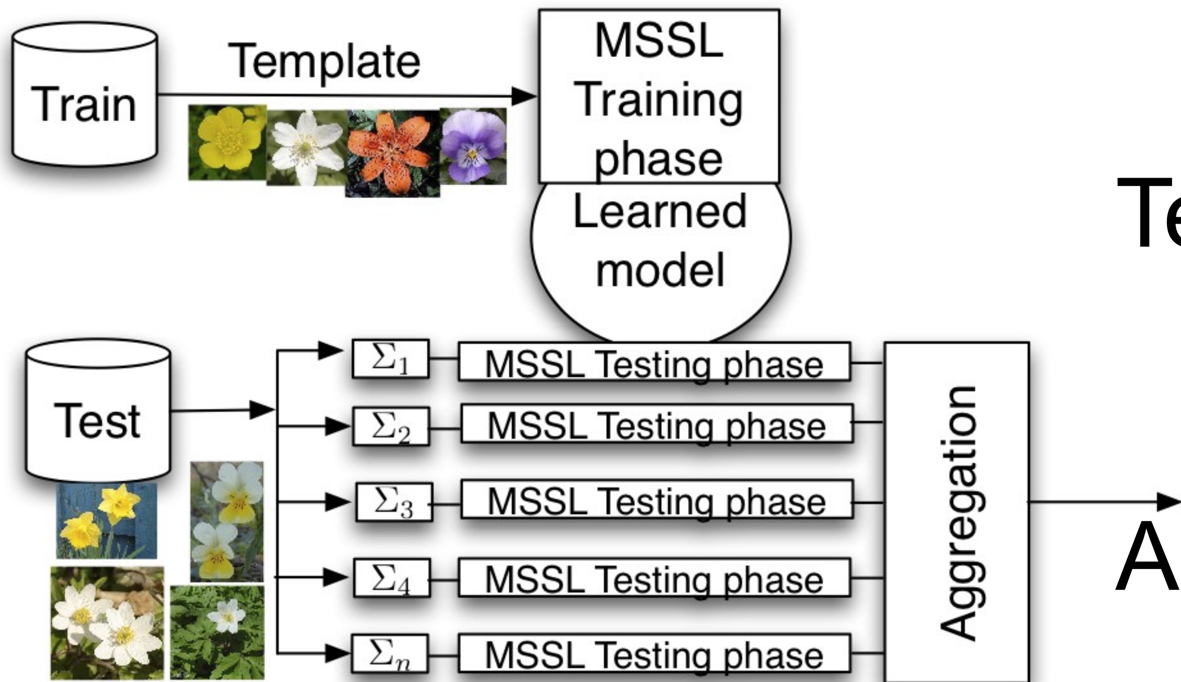
- With MSSL we have learned relationships between pixels belonging to an object for a concrete training set.

Classifying Objects at different sizes

Problem:

- Relationships between pixels change if object size changes.
- It is not possible to learn at all possible sizes?

Learning at multiple scales



Train: templates -> training images at same scale.

Test: shift scales -> perform several testing phases shifting scales.

Aggregation: Maximum likelihood value for each pixel.

Experiments

Validation Experiment: horses

Training phase: Horse Images

Testing phase: Same horse images resized to its half size.

Train

MSSL Result

Test

Scales {2,4,8}

Scales {1,2,4}

Flowers classification

Training phase:

- Flower template. 16 images at same size.
- Only color features, no spatial features.
- Adaboost classifiers.
- Scales $= \sum\{18,27,41\}$.

Testing phase:

- Scales $= \sum\{0.5,3,5,8,12,18,27,41\}$.
- 6 testing rounds per image.

Aggregation:

- Take the maximum for all rounds.

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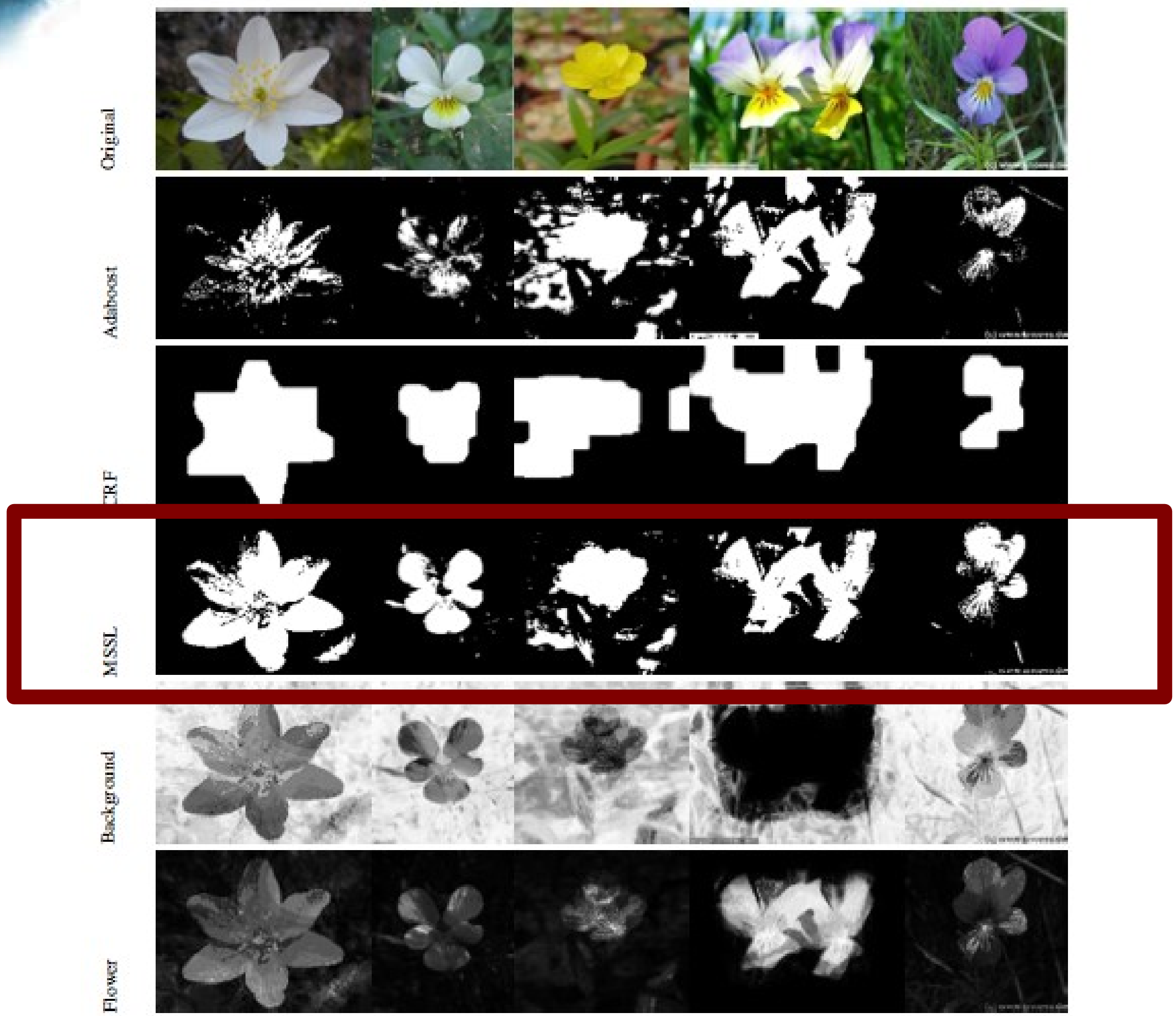

Method	Acc	Over	Sens	Spec	Prec	NPV
ADABoost	0,8773	0,5621	0,9207	0,7217	0,9222	0,7176
CRF	0,8568	0,5840	0,8430	**0,9052**	**0,9689**	0,6220
MSSL	**0,9012**	**0,6243**	**0,9427**	0,7524	0,9317	**0,7858**

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Conclusions

- Multiscale Stacked Sequential Learning is a useful framework for object classification task.
- Results are comparable with those of the state-of-the-art methodologies like CRF.
- Without retraining we can classify correctly images at differents scales, only performing some extra test rounds.