

Towards Machine Learning in NowCastMIX

... learning to make something learned ...


Bölöni Gergely, DWD, FE22

Towards Machine Learning in NowCastMIX

... learning to make something learned ...


Write a four line poem about the relationship of severe weather warning and machine learning

< 2/2 >


 Machine learning predicts the storm's fierce might,
Data-driven insights guide through the night,
Algorithms warn, safeguarding our way,
Human and tech united, weather kept at bay.

Írj egy négysoros verset a viharjelzés és a gépi tanulás kapcsolatáról

< 2/2 >

 Viharjelzés pontosságát gép tanulja meg,
Adatkból jósol, mint bölcs jó, figyel,
Algoritmusokban az előrejelzés rejlik,
Ember és gép együtt, vihartól nem félünk.

Írj egy négysoros verset a viharjelzés és a gépi tanulás kapcsolatáról de csak magyar nyelvű szövegen tanulj

 Gépi tanulás szélvésztt fürkészh,
Adatkból épít jövőt és igézh,
Pontosan jósol, viharjelzést ad,
Biztonságot nyújt, míg az ég harcba száll.

ChatGPT-4

Böloni Gergely, DWD, FE22



NowCastMIX in a nutshell

OCTOBER 2018

JAMES ET AL.

1413

NowCastMIX: Automatic Integrated Warnings for Severe Convection on Nowcasting Time Scales at the German Weather Service

PAUL M. JAMES, BERNHARD K. REICHERT, AND DIRK HEIZENREDER

Deutscher Wetterdienst, Offenbach, Germany

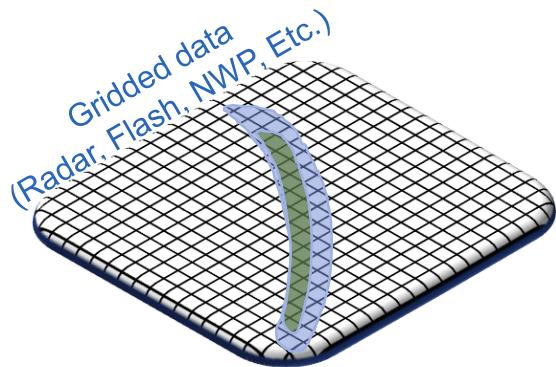
(Manuscript received 9 March 2018, in final form 15 August 2018)

ABSTRACT

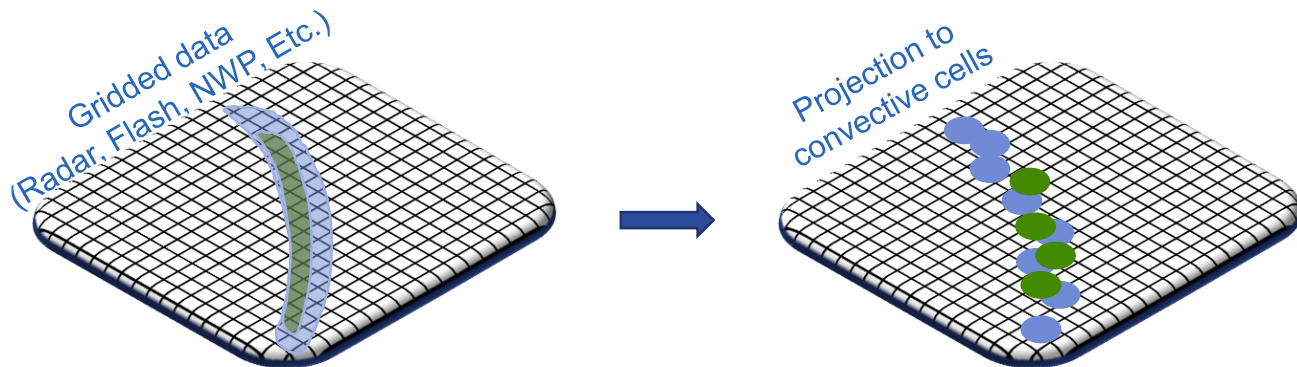
NowCastMIX is the core nowcasting guidance system at the German Weather Service. It automatically monitors several systems to capture rapidly developing high-impact mesoscale convective events, including 3D radar volume scanning, radar-based cell tracking and extrapolation, lightning detection, calibrated precipitation extrapolations, NWP, and live surface station reports. Within the context of the larger warning decision support process AutoWARN, NowCastMIX integrates the input data into a high-resolution analysis, based on a fuzzy logic approach for thunderstorm categorization and extrapolation, to provide an optimized warning solution with a 5-min update cycle for lead times of up to 1 h. Feature tracking is undertaken to optimize the direction of warning polygons, allowing individual, tangentially moving cells or cell clusters to be tracked explicitly. An adaptive ensemble clustering is deployed to reduce the spatial complexity of the resulting warning fields and smooth noisy temporal variations to a manageable level for duty forecasters. Further specialized outputs for civil aviation and for a public mobile phone warning app are generated. Now in its eighth year of operation, a comprehensive and complete set of thunderstorm analyses and nowcasts over Germany has been created, which is of unique value for ongoing research and development efforts for improving the system, as well as for addressing climatological aspects of severe convection. Verification has shown that NowCastMIX has helped to significantly improve the quality of the official warnings for severe convective weather events when used within the AutoWARN process.

James et al., 2018, WAF

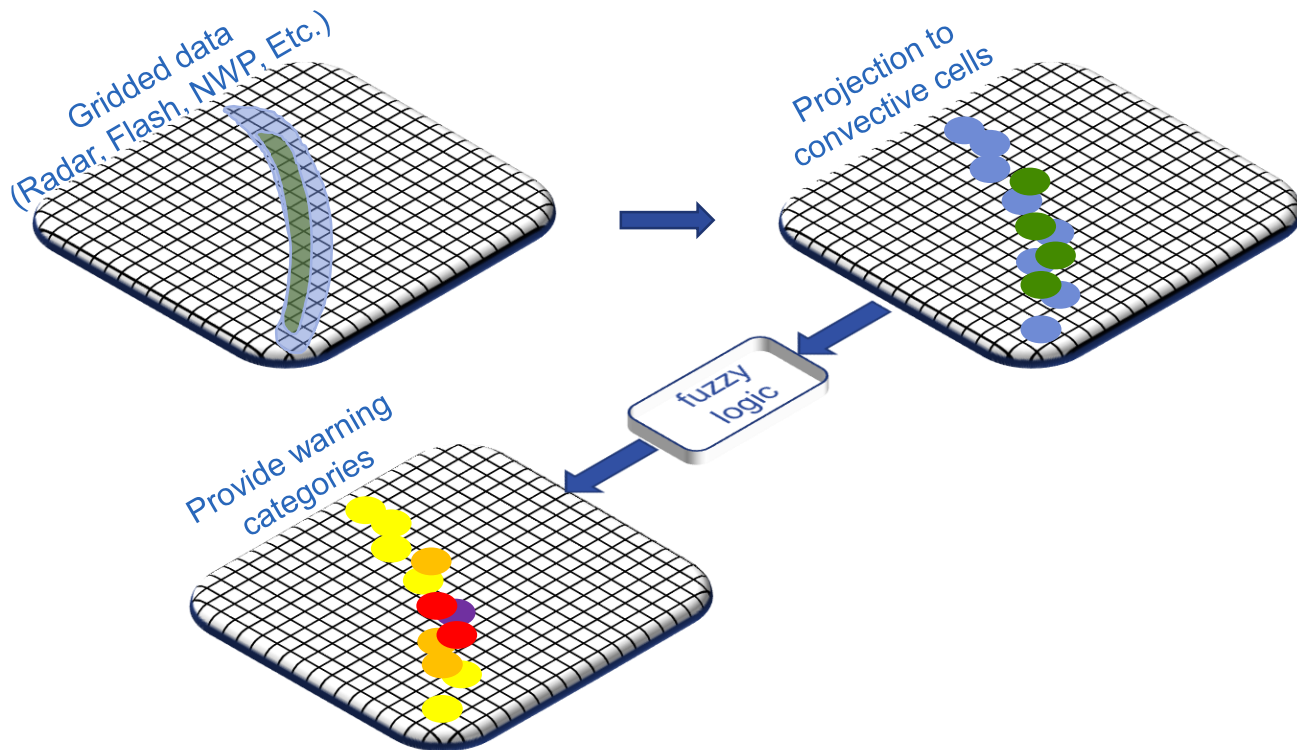
NowCastMIX in a nutshell



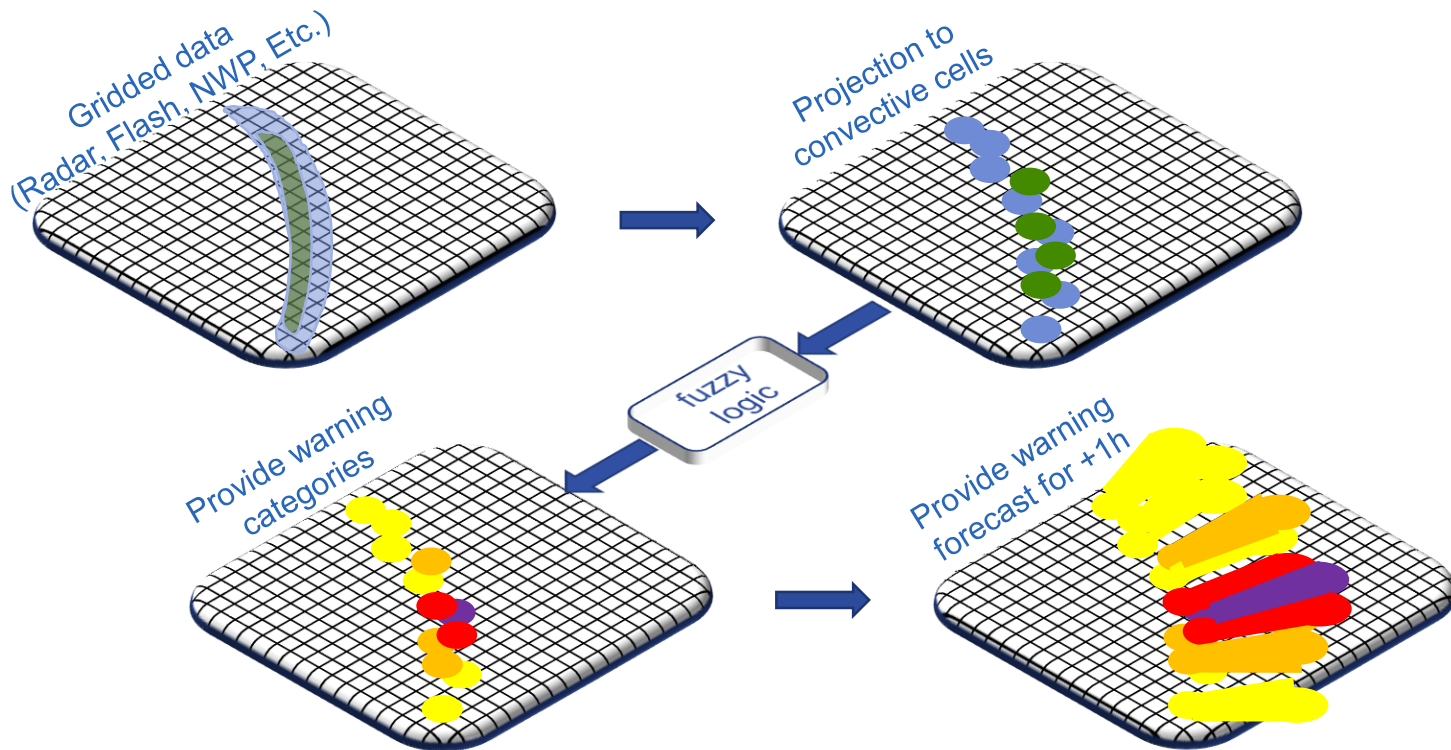
NowCastMIX in a nutshell



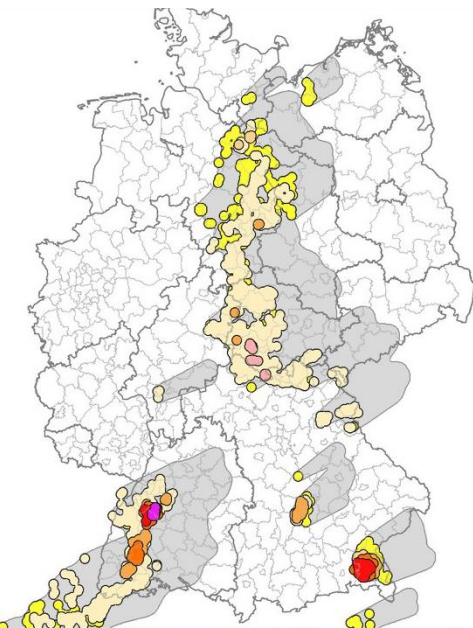
NowCastMIX in a nutshell



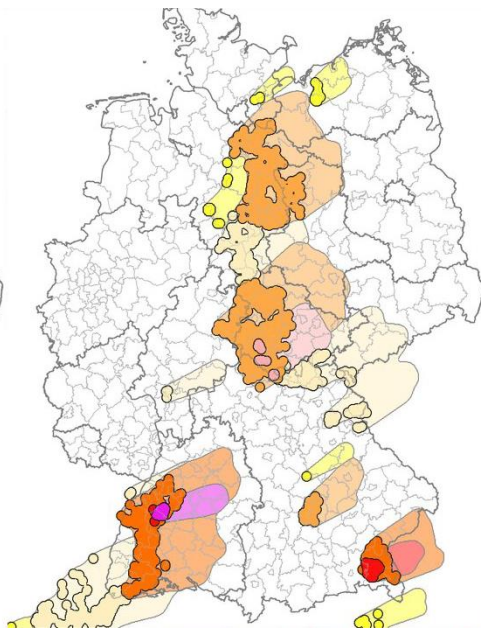
NowCastMIX in a nutshell



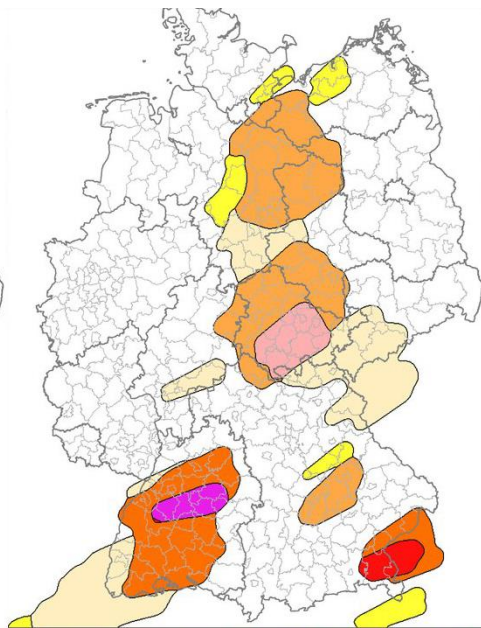
NowCastMIX in a nutshell



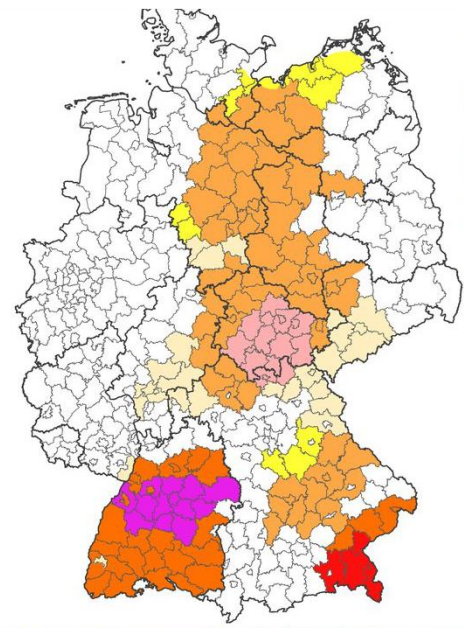
Analysis + Warning areas



Clusters + Warning polygons



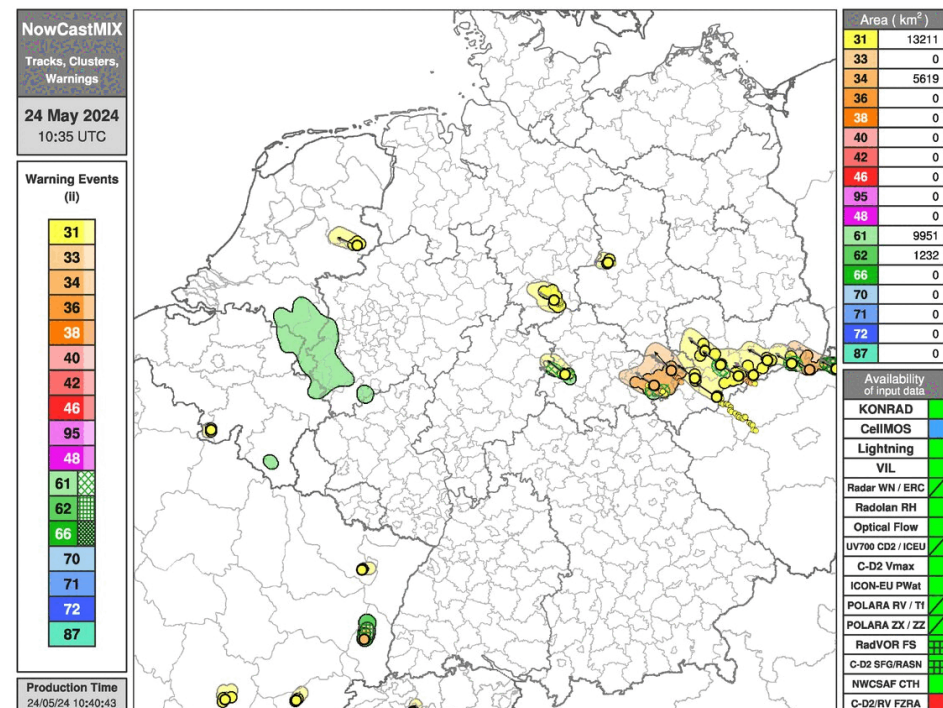
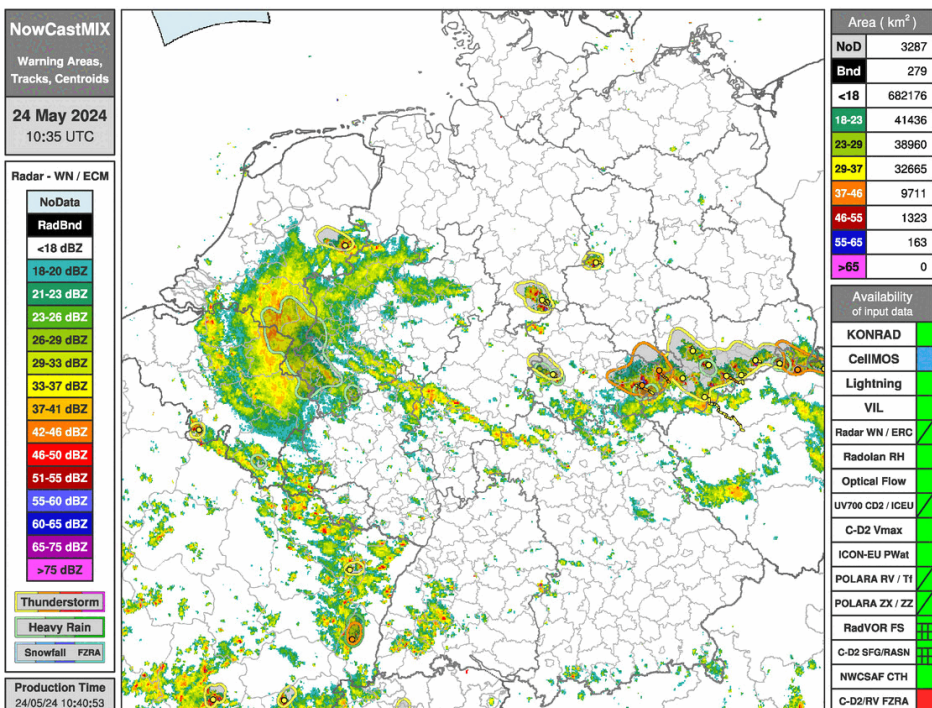
Warning suggestion for the next hour



Example: projection on counties

courtesy: Paul James

NowCastMIX in a nutshell



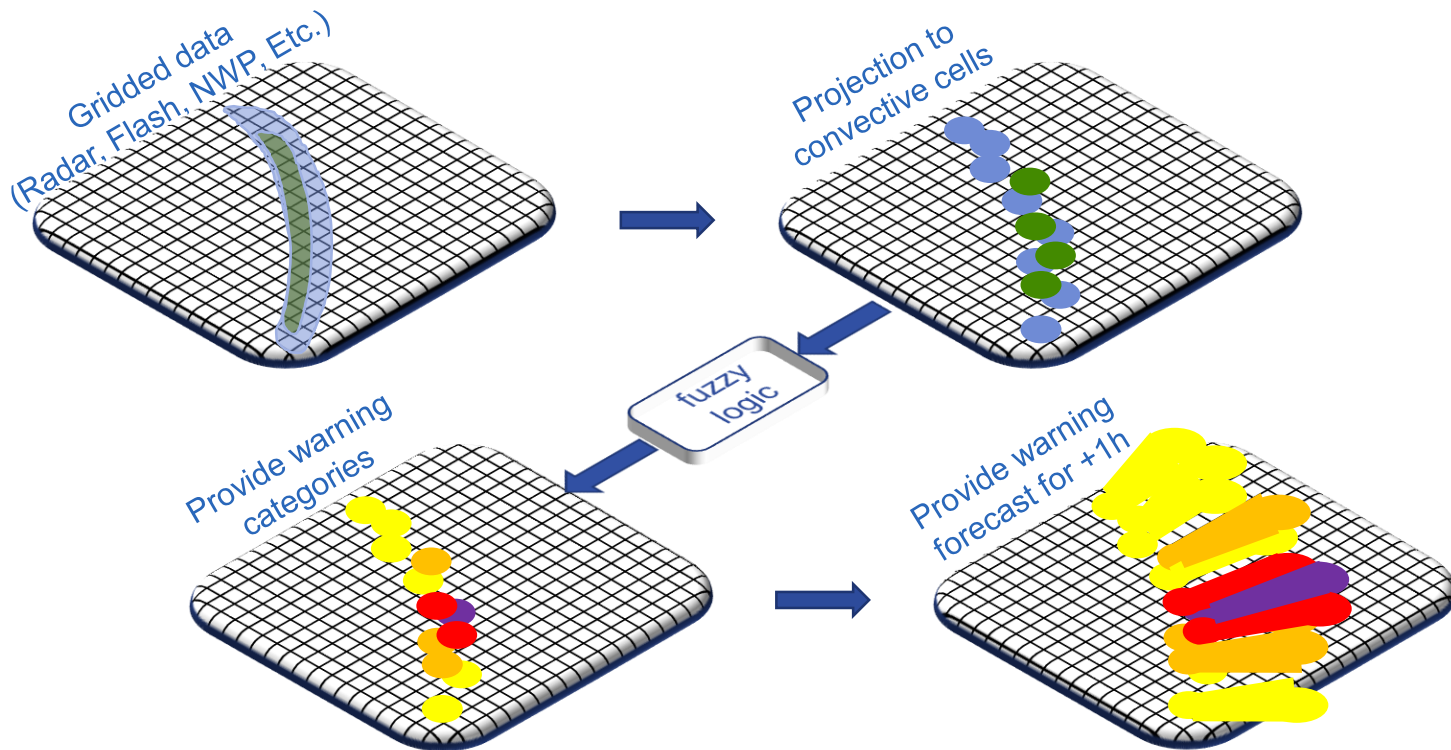
Disclaimer

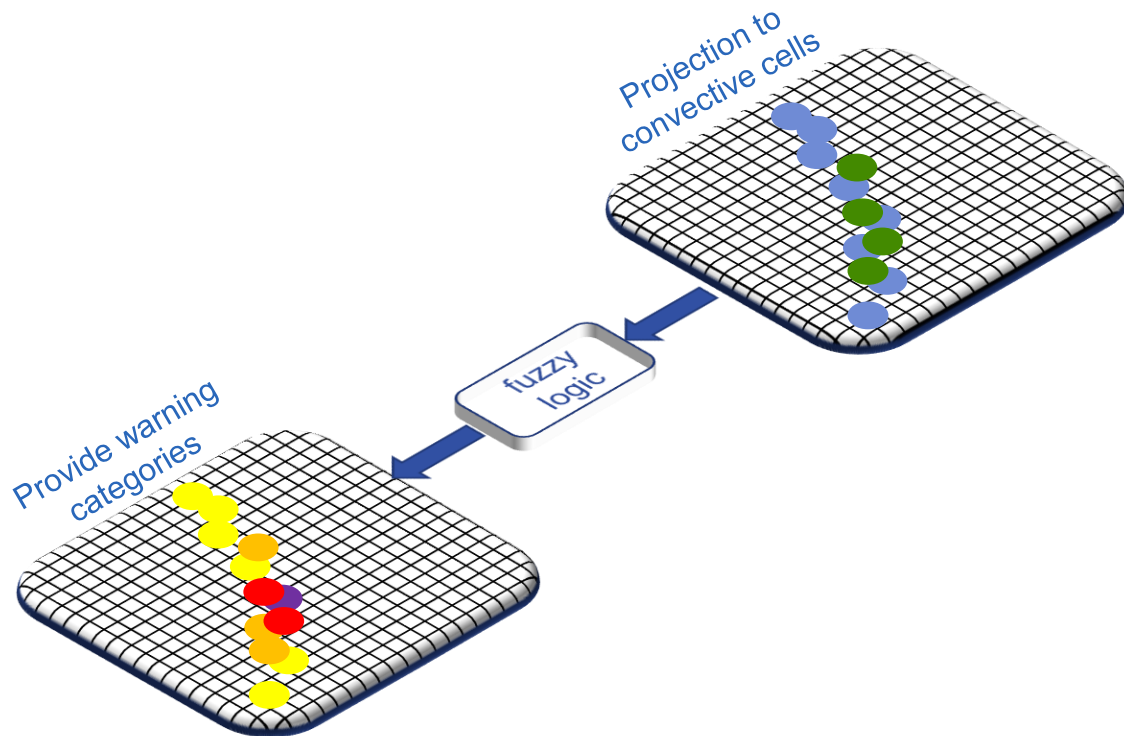


gifdb.com

EXPERIMENTAL!

Motivation

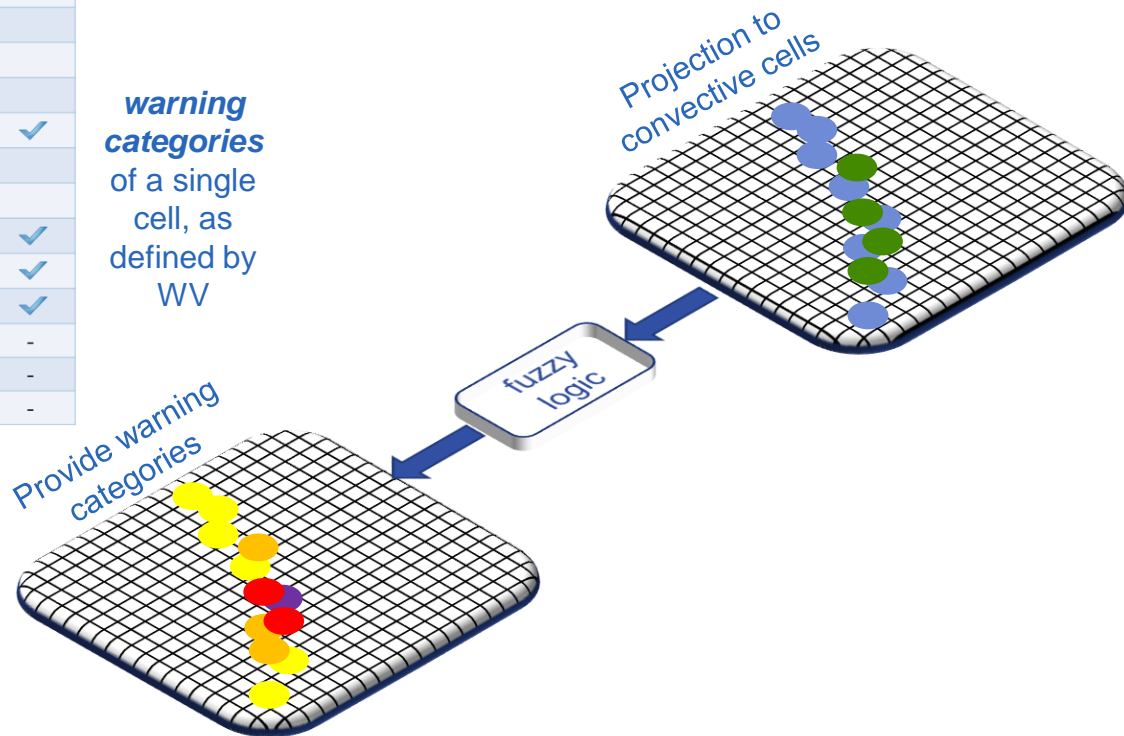




Motivation

| ii | Böen Bft. | Regen mm/h | Hagel |
|----|--------------|---------------|-------|
| 31 | ≤ 7 | <15 | |
| 33 | ≤ 10 | <15 | |
| 34 | ≤ 7 | 15-25 | |
| 36 | ≤ 10 | 15-25 | |
| 38 | ≤ 10 | 15-25 | ✓ |
| 40 | ≤ 12+ | <15 | |
| 42 | ≤ 9 | 25-40 | |
| 46 | ≤ 10 | 25-40 | ✓ |
| 95 | ≤ 9 | >40 | ✓ |
| 48 | ≤ 12+ | >25-40 | ✓ |
| 61 | - | 15-25 | - |
| 62 | - | 25-40 | - |
| 66 | - | >40 | - |

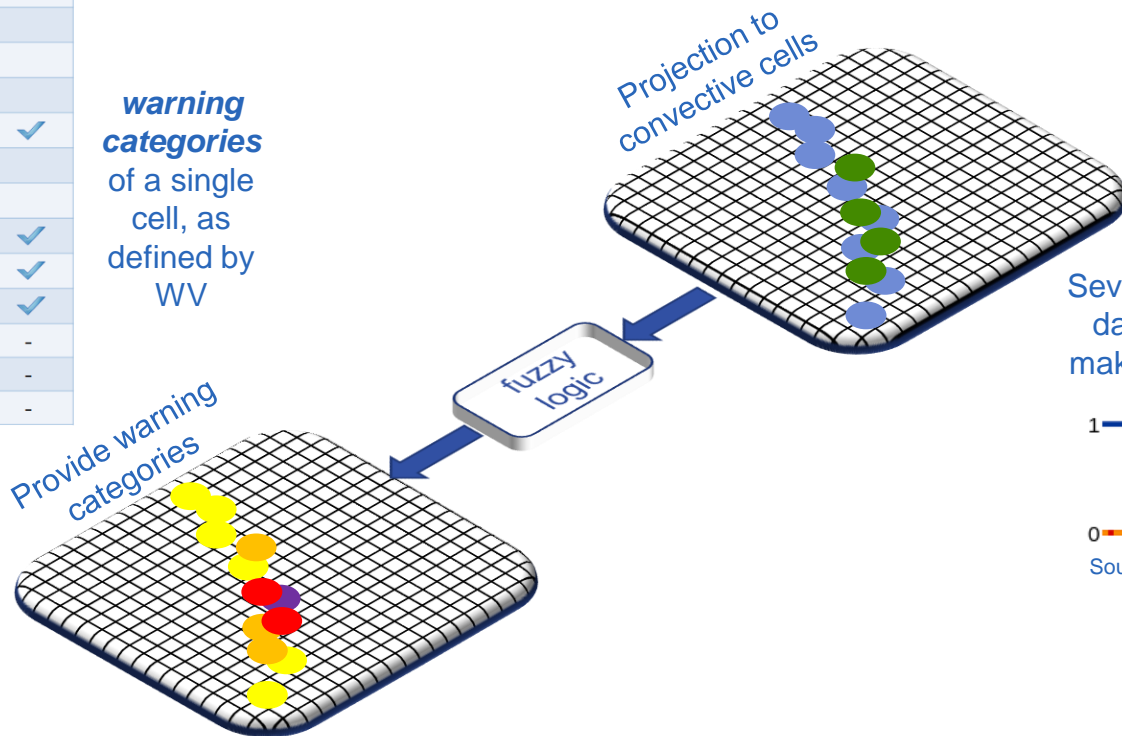
*warning
categories
of a single
cell, as
defined by
WV*



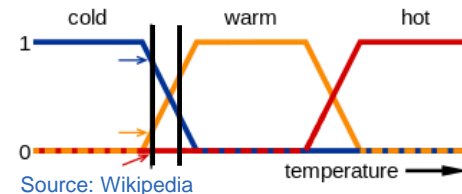
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warning categories of a single cell, as defined by WV



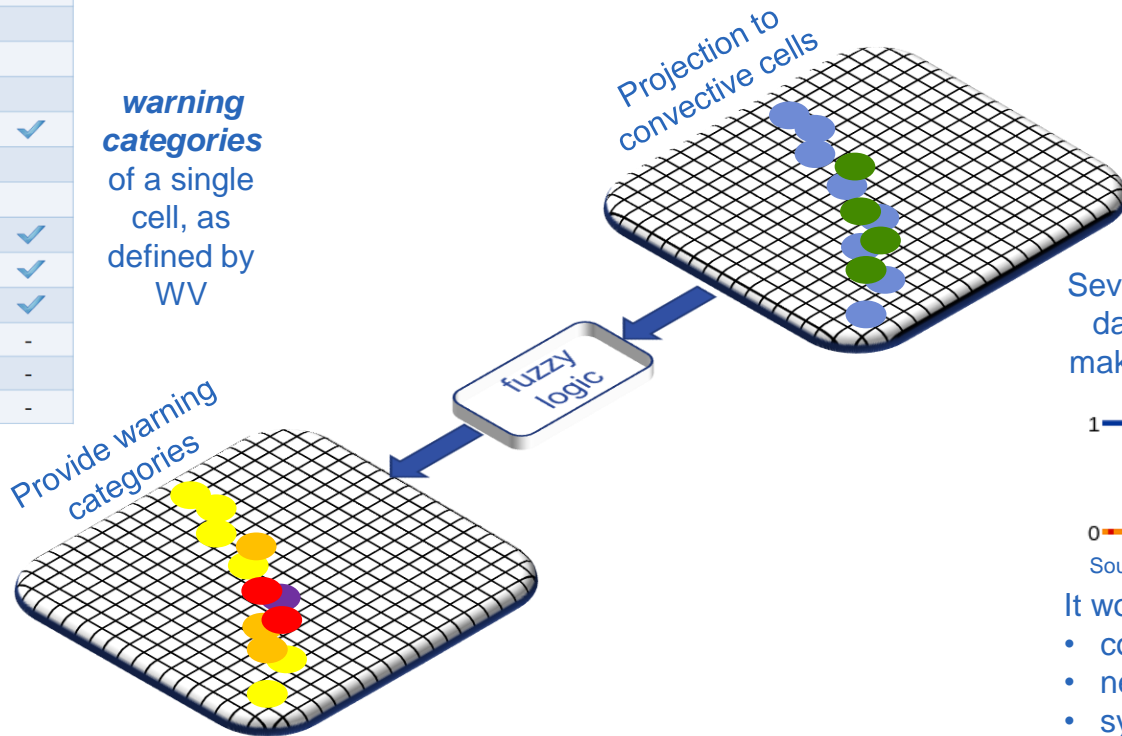
Fuzzy Logic:
Several (possibly contradicting) data sources at the same time makes the categorization *fuzzy*...



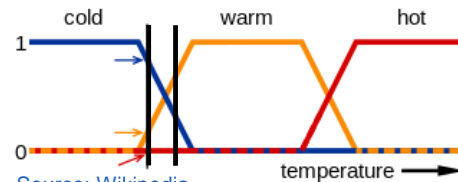
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warning categories of a single cell, as defined by WV



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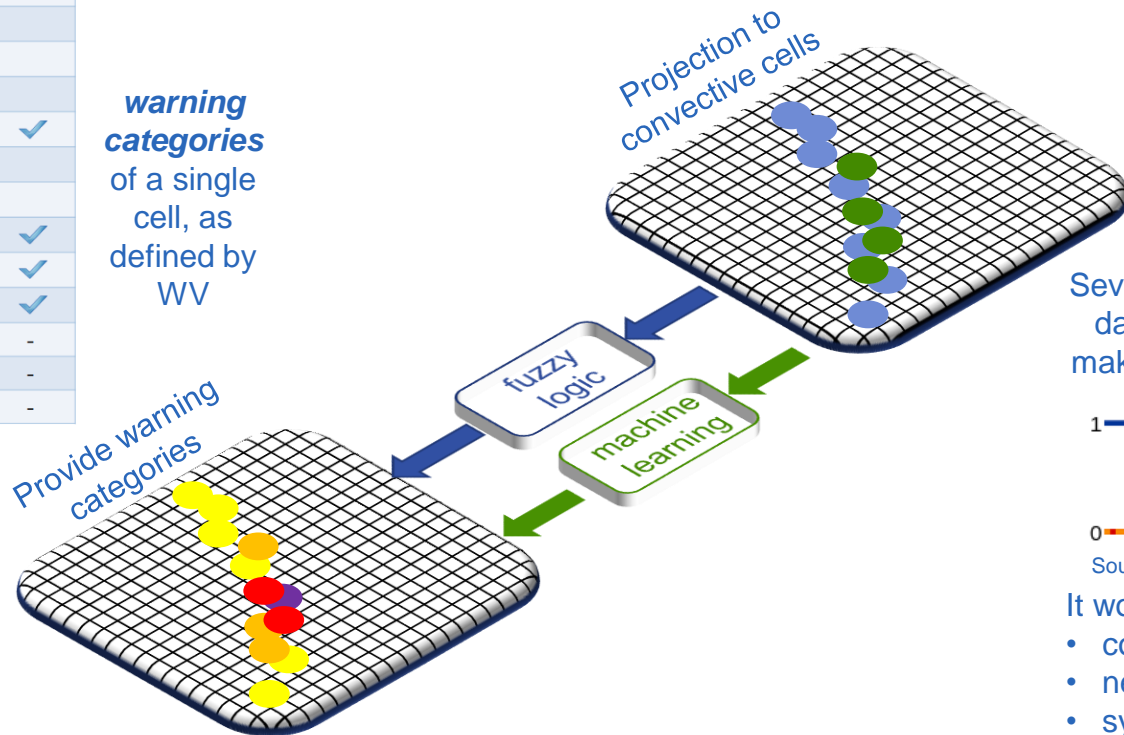
It works well, but:

- complex
- new data → expert tuning
- system upgrades → expert tuning

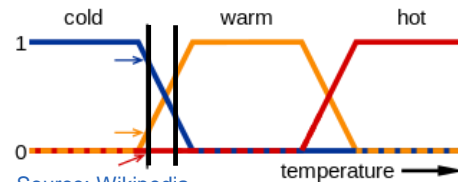
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It works well, but:

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Features:

Meteorological state at cell centres

| Variable | Source |
|-----------------------|--|
| Time (yy,mm,dd,hh,mm) | Cell occurrence |
| Location (lat, lon) | Cell location |
| Wind (speed, dir) | KONRAD3D AutoRadSatW ZVF ICON-D2 V-CVF |
| Precipitation | Radolan RH Radolan RW |
| Precipitable Water | Radar (VIL) ICON-D2 |
| Hail flag | KONRAD 3D |
| Cell category | KONRAD3D |
| Flash rate | LINET |
| Cloud-top height | NWC-SAF |



machine learning:
classification
problem



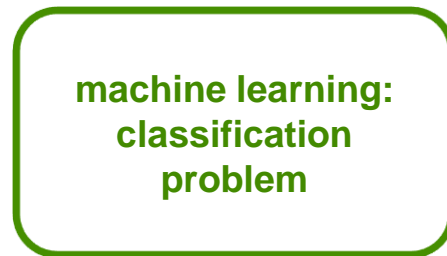
Target (fuzzy-logic):
warning categories

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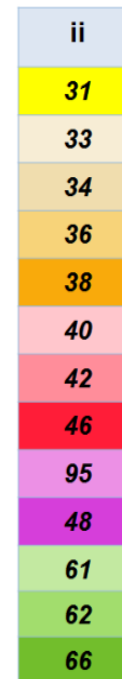
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Target (fuzzy-logic): warning categories

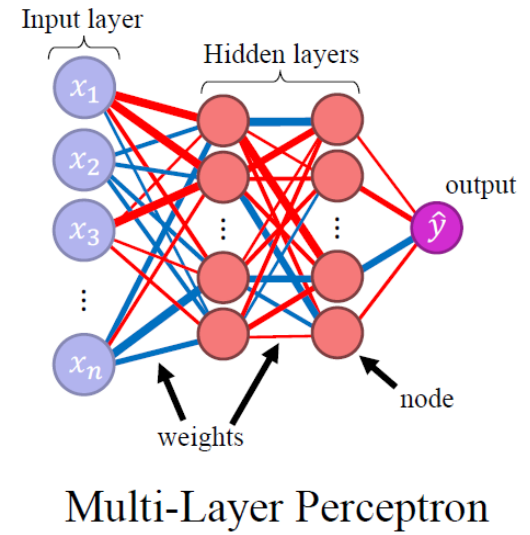
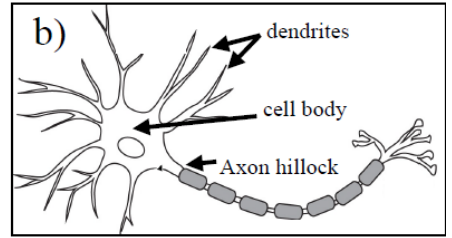
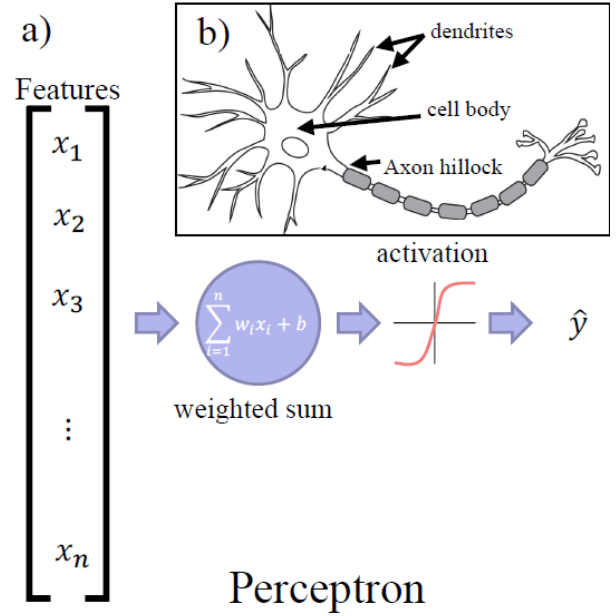


NowCastMIX archive:

- ~ 5 years of labeled data
- ~ 10^6 data instances / year
- ground truth: fuzzy-logic!

My ANN learning process

My ANN learning process



How good is my prediction?
→ Loss function:

$$f(x, w) = (\hat{y}_t - \hat{y}_p)^2$$

How can I improve it?
→ Loss function gradient:

$$\nabla_w f(x, w) = \dots$$

→ Gives *sensitivity* to w i.e. *direction* for nudging w so that the loss will be smaller

Chase et al., 2023

1.17. Neural network models (supervised)

Warning: This implementation is not intended for large-scale applications. In particular, scikit-learn offers no GPU support. For much faster, GPU-based implementations, as well as frameworks offering much more flexibility to build deep learning architectures, see [Related Projects](#).

1.17.1. Multi-layer Perceptron

Multi-layer Perceptron (MLP) is a supervised learning algorithm that learns a function $f(\cdot) : \mathbb{R}^m \rightarrow \mathbb{R}^o$ by training on a dataset, where m is the number of dimensions for input and o is the number of dimensions for output. Given a set of features $\mathbf{X} = \mathbf{x}_1, \mathbf{x}_2, \dots, \mathbf{x}_m$ and a target \mathbf{y} , it can learn a non-linear function approximator for either classification or regression. It is different from logistic regression, in that between the input and the output layer, there can be one or more non-linear layers, called hidden layers. Figure 1 shows a one hidden layer MLP with scalar output.

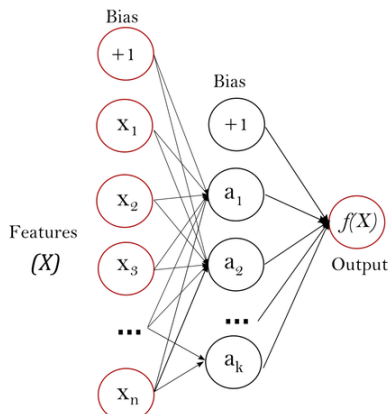


Figure 1 : One hidden layer MLP.

Tool:



- Free / open source @ GitHub
- Commercially usable
- Python (based on Numpy, Scipy)
- Runs on CPU (not on GPU)
- Not meant for large-scale problems

My ANN learning process

How do I set up my ANN?



My ANN learning process

How do I set up my ANN?



I need a „toy problem“ to figure out...

My ANN learning process

My „toy problem“ (MLPfog):

- fog detection
- synthetic random data:
T, Td, FF
- simple physical model:

```
if T == Td and FF < 0.8
    fog = 1
else
    fog = 0
```
- ML model (ANN/MLP scikit-learn) to learn what the physical model does (single class classification)

My ANN learning process

My „toy problem“ (MLPfog):

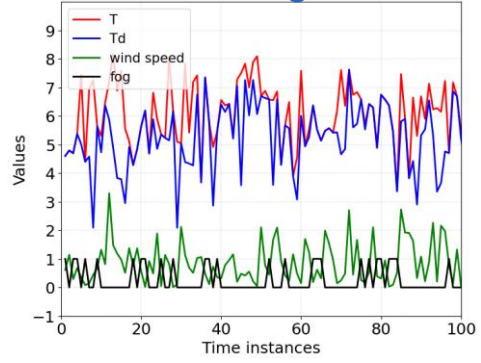
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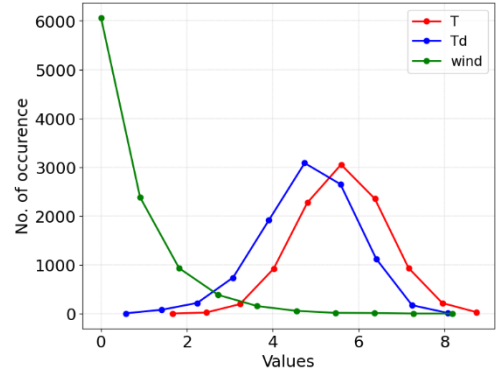
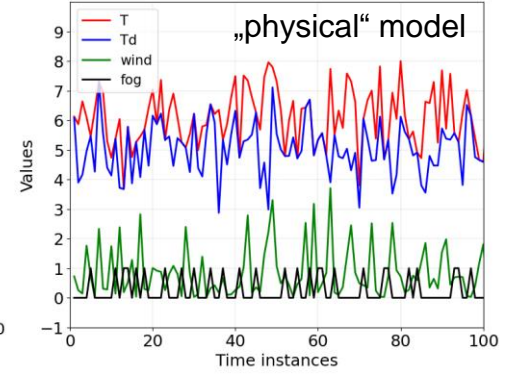
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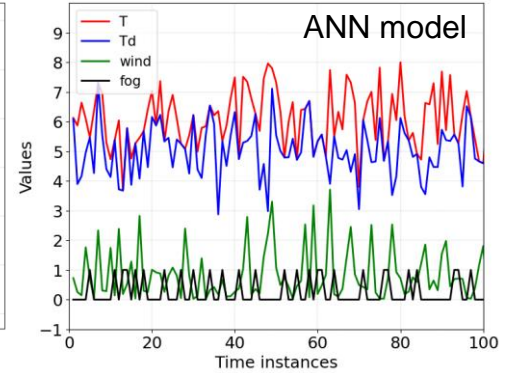
Training set



Validation set



ANN model



My ANN learning process

Verification

| | observation | | |
|----------|-------------|-----|----|
| estimate | | Yes | No |
| | Yes | a | b |
| | No | c | d |

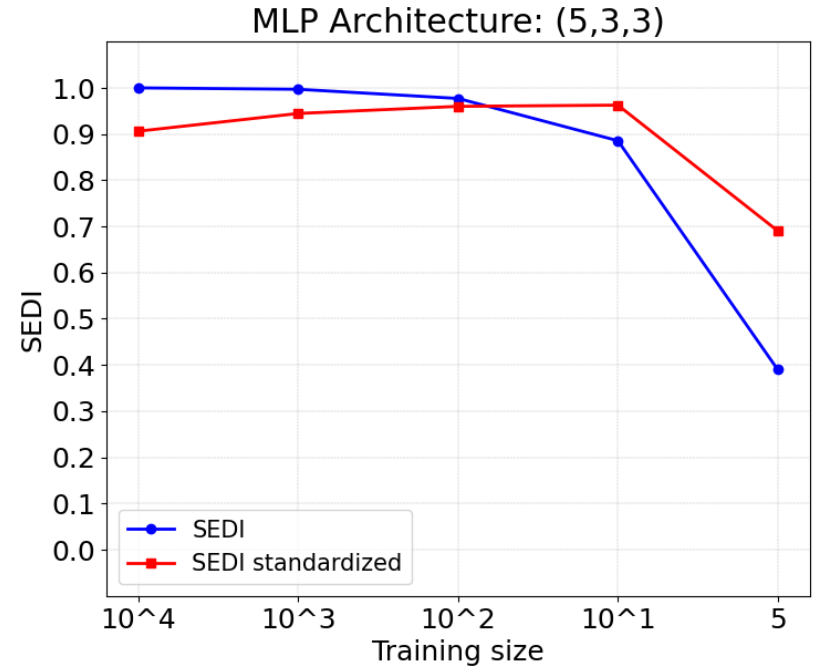
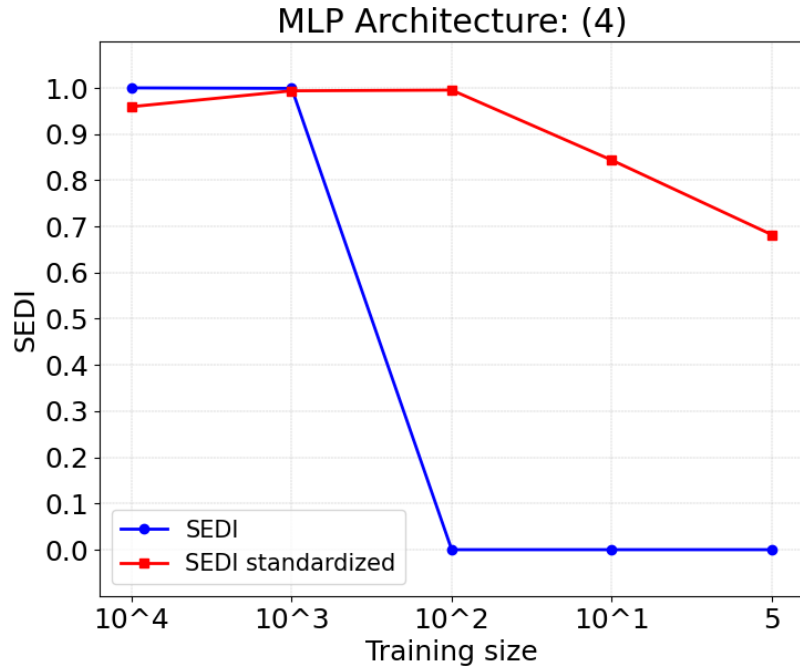
Probability Of Detection: $POD = \frac{a}{(a+c)}$

False Alarm Rate: $FAR = \frac{b}{(b+d)}$

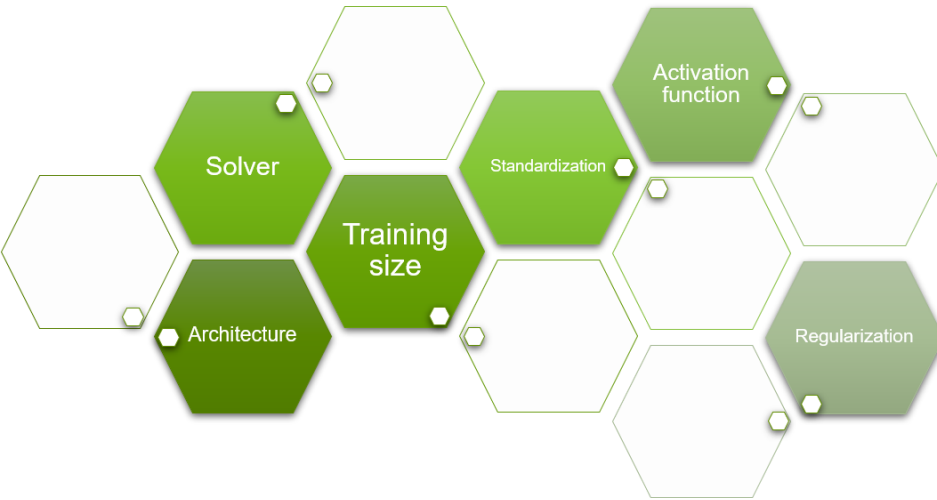
Symmetric Extremal Dependency Index: $SEDI = \frac{\ln(FAR) - \ln(POD) - \ln(1-FAR) + \ln(1-POD)}{\ln(FAR) + \ln(POD) + \ln(1-FAR) + \ln(1-POD)}$

My ANN learning process

Question: How important standardization w.r.t. the training size?



How do I set up my ANN?

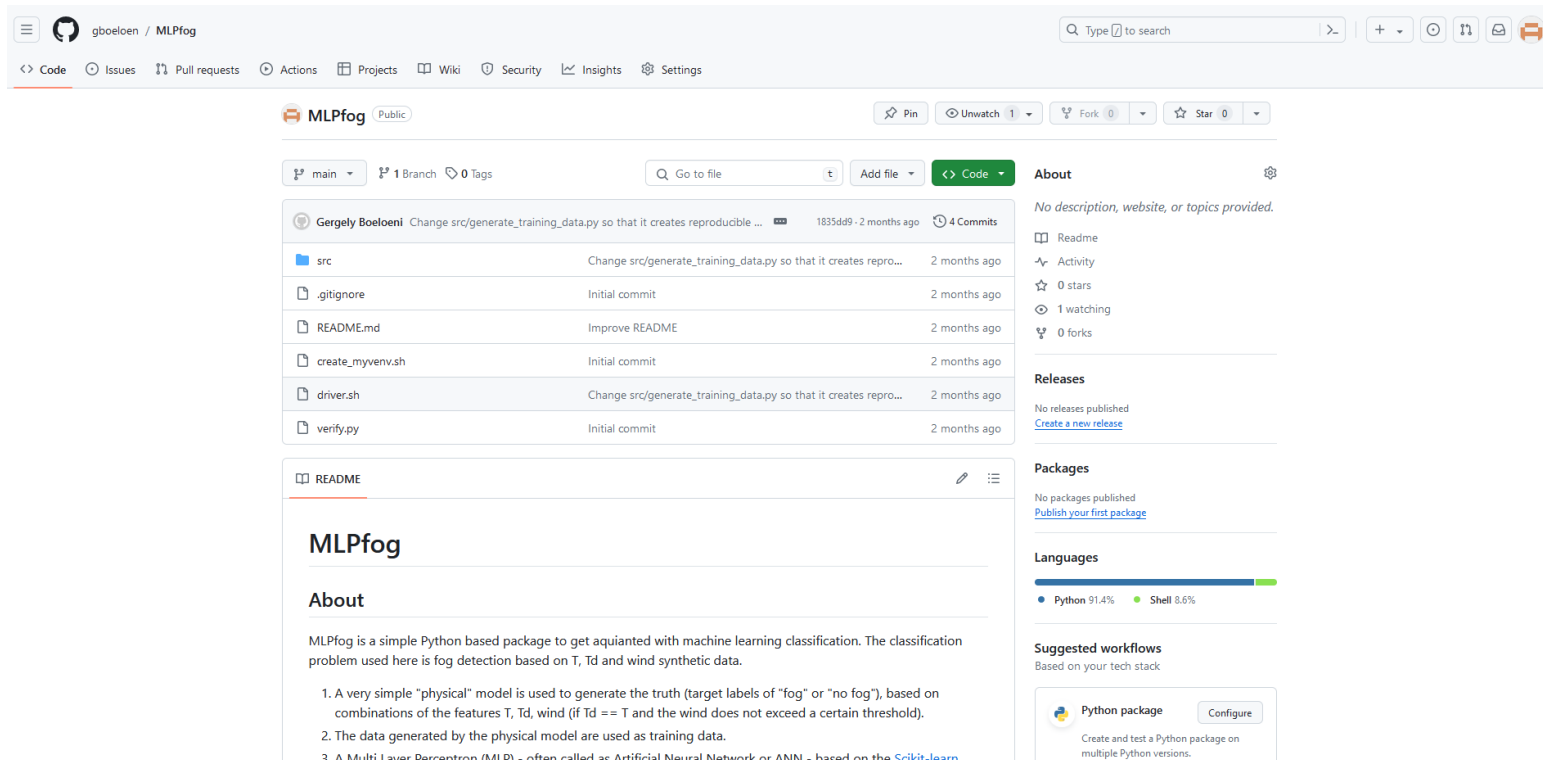


Some vague answers:

- **by experience** (rather „trial & error“ than a logic based approach, did not find any valid rules of thumb, lack of deeper understanding...)
- **experience (a set-up) not transferable from small-size problems to large-size problems**
- **risk of missing important (or most relevant) settings is non-negligible**

My ANN learning process

MLPfog: <https://github.com/gboeloen/MLPfog>



The screenshot shows the GitHub repository page for MLPfog. The repository is public and has 4 commits. The file list includes src, .gitignore, README.md, create_myvenv.sh, driver.sh, and verify.py. The README file is selected, showing the title "MLPfog" and an "About" section. The "About" section describes MLPfog as a simple Python-based package for machine learning classification, used for fog detection. It lists three points: 1. A simple physical model for generating truth labels. 2. Training data from the physical model. 3. A Multi-Layer Perceptron (MLP) model based on Scikit-Learn. The right sidebar shows the repository's activity, including no releases published and no packages published. A suggested workflow for Python packages is also visible.

gboeloen / MLPfog

main 1 Branch 0 Tags

Go to file Add file Code

Gergely Boeloen Change src/generate_training_data.py so that it creates reproducible ... 1835d9 · 2 months ago 4 Commits

- src Change src/generate_training_data.py so that it creates repro... 2 months ago
- .gitignore Initial commit 2 months ago
- README.md Improve README 2 months ago
- create_myvenv.sh Initial commit 2 months ago
- driver.sh Change src/generate_training_data.py so that it creates repro... 2 months ago
- verify.py Initial commit 2 months ago

README

MLPfog

About

MLPfog is a simple Python based package to get acquainted with machine learning classification. The classification problem used here is fog detection based on T, Td and wind synthetic data.

1. A very simple "physical" model is used to generate the truth (target labels of "fog" or "no fog"), based on combinations of the features T, Td, wind (if Td == T and the wind does not exceed a certain threshold).
2. The data generated by the physical model are used as training data.
3. A Multi-Layer Perceptron (MLP) - often called as Artificial Neural Network or ANN - based on the [Scikit-Learn](#)

About

No description, website, or topics provided.

- Readme
- Activity
- 0 stars
- 1 watching
- 0 forks

Releases

No releases published
[Create a new release](#)

Packages

No packages published
[Publish your first package](#)

Languages

- Python 91.4%
- Shell 8.6%

Suggested workflows

Based on your tech stack

Python package Configure

Create and test a Python package on multiple Python versions.



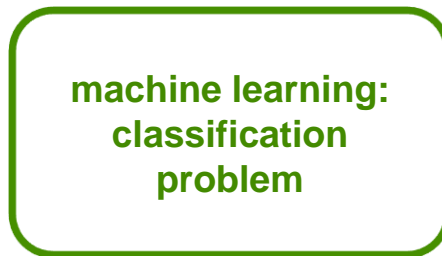
ML for emulating NowCastMIX Fuzzy-logic

ML for emulating NCM Fuzzy-logic

Features:

Meteorological state at cell centres

| Variable | Source |
|-----------------------|--|
| Time (yy,mm,dd,hh,mm) | Cell occurrence |
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| Hail flag | KONRAD 3D |
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| Flash rate | LINET |
| Cloud-top height | NWC-SAF |



Target (fuzzy-logic): warning categories

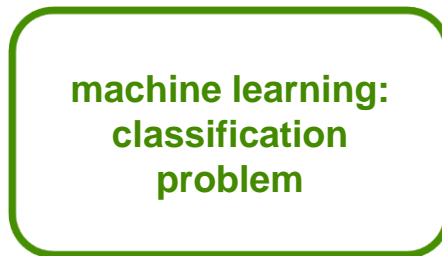
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ML for emulating NCM Fuzzy-logic

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New w.r.t. MLPfog:

- 10+ target labels → **multiclass classification**
- larger amount & variety of features
- computationally more expensive (training)

- **Inherently multiclass:**

- `naive_bayes.BernoulliNB`
- `tree.DecisionTreeClassifier`
- `tree.ExtraTreeClassifier`
- `ensemble.ExtraTreesClassifier`
- `naive_bayes.GaussianNB`
- `neighbors.KNeighborsClassifier`
- `semi_supervised.LabelPropagation`
- `semi_supervised.LabelSpreading`
- `discriminant_analysis.LinearDiscriminantAnalysis`
- `svm.LinearSVC` (setting `multi_class="crammer_singer"`)
- `linear_model.LogisticRegression` (setting `multi_class="multinomial"`)
- `linear_model.LogisticRegressionCV` (setting `multi_class="multinomial"`)
- `neural_network.MLPClassifier`
- `neighbors.NearestCentroid`
- `discriminant_analysis.QuadraticDiscriminantAnalysis`
- `neighbors.RadiusNeighborsClassifier`
- `ensemble.RandomForestClassifier`
- `linear_model.RidgeClassifier`
- `linear_model.RidgeClassifierCV`

- **Multiclass as One-Vs-One:**

- `svm.NuSVC`
- `svm.SVC`
- `gaussian_process.GaussianProcessClassifier` (setting `multi_class = "one_vs_one"`)

- **Multiclass as One-Vs-The-Rest:**

- `ensemble.GradientBoostingClassifier`
- `gaussian_process.GaussianProcessClassifier` (setting `multi_class = "one_vs_rest"`)
- `svm.LinearSVC` (setting `multi_class="ovr"`)
- `linear_model.LogisticRegression` (setting `multi_class="ovr"`)
- `linear_model.LogisticRegressionCV` (setting `multi_class="ovr"`)
- `linear_model.SGDClassifier`
- `linear_model.Perceptron`
- `linear_model.PassiveAggressiveClassifier`

ML for emulating NCM Fuzzy-logic



Multiclass classification with

Inherently multiclass:

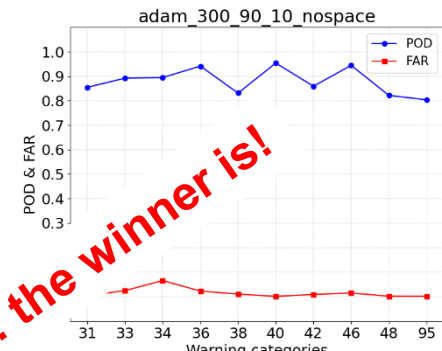
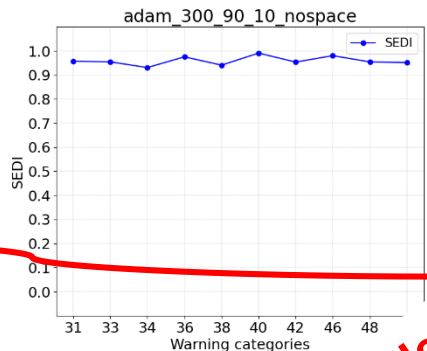
- naive_bayes.BernoulliNB
- tree.DecisionTreeClassifier
- tree.ExtraTreeClassifier
- ensemble.ExtraTreesClassifier
- naive_bayes.GaussianNB
- neighbors.KNeighborsClassifier
- semi_supervised.LabelPropagation
- semi_supervised.LabelSpreading
- discriminant_analysis.LinearDiscriminantAnalysis
- svm.LinearSVC (setting multi_class="crammer_singer")
- linear_model.LogisticRegression (setting multi_class="multinomial")
- linear_model.LogisticRegressionCV (setting multi_class="multinomial")
- **neural_network.MLPClassifier**
- neighbors.NearestCentroid
- discriminant_analysis.QuadraticDiscriminantAnalysis
- neighbors.RadiusNeighborsClassifier
- ensemble.RandomForestClassifier
- linear_model.RidgeClassifier
- linear_model.RidgeClassifierCV

Multiclass as One-Vs-One:

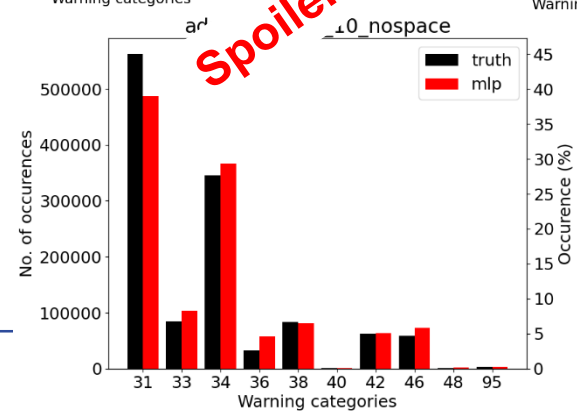
- svm.NuSVC
- svm.SVC
- gaussian_process.GaussianProcessClassifier (setting multi_class = "one_vs_one")

Multiclass as One-Vs-The-Rest:

- ensemble.GradientBoostingClassifier
- gaussian_process.GaussianProcessClassifier (setting multi_class = "one_vs_rest")
- svm.LinearSVC (setting multi_class="ovr")
- linear_model.LogisticRegression (setting multi_class="ovr")
- linear_model.LogisticRegressionCV (setting multi_class="ovr")
- linear_model.SGDClassifier
- linear_model.Perceptron
- linear_model.PassiveAggressiveClassifier

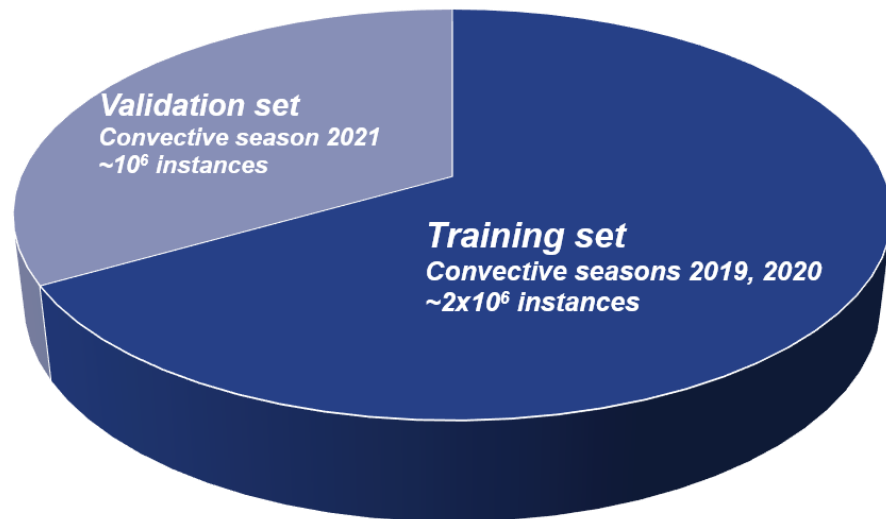


Spoiler: the winner is!



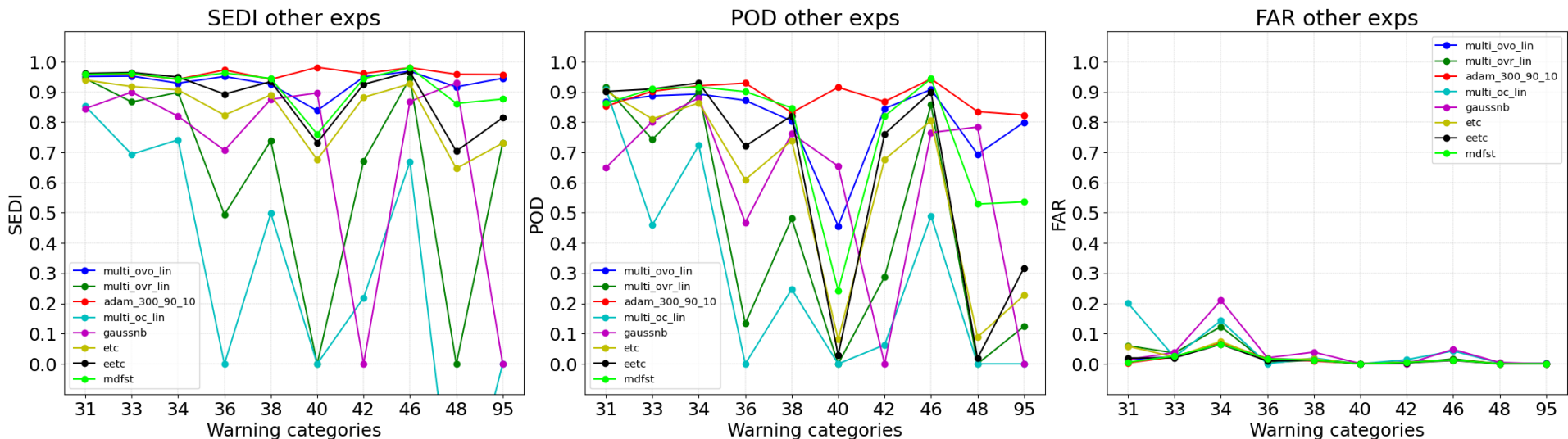
Experimental setup

- offline tests (100% Python - not yet in the NowCastMIX code)
- separate training & validation set
- verification of each (10) warning category via SEDI (POD & FAR)
- check distribution of warning categories
- check distribution of missed events for each warning category



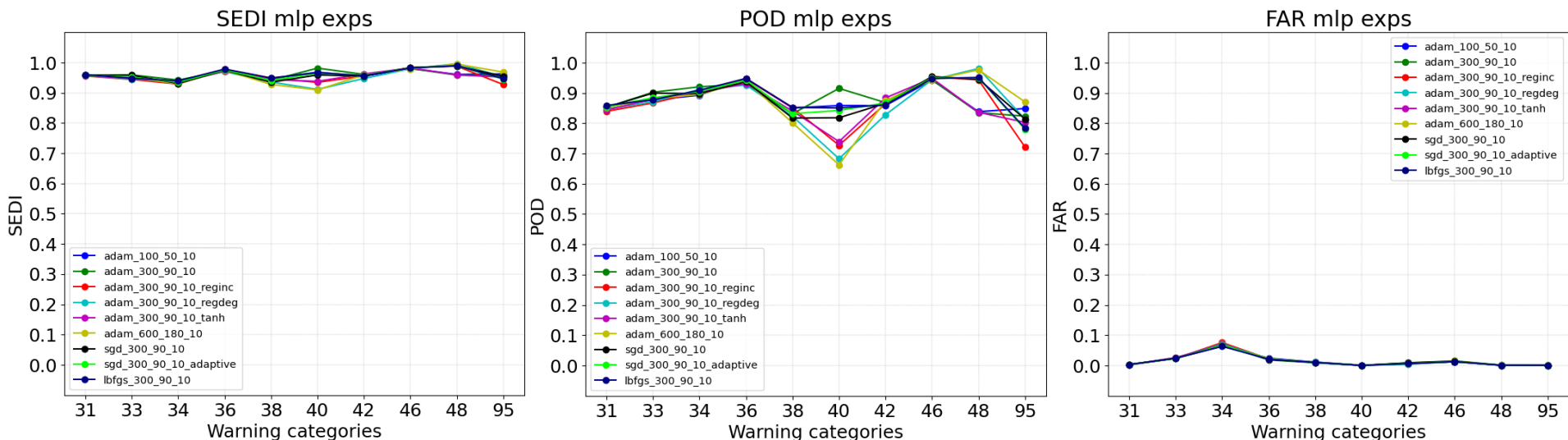
ML for emulating NCM Fuzzy-logic

Sensitivity to *ML method* (ANN softmax, svm, decision tree, random forest, GaussNB, etc.)



ML for emulating NCM Fuzzy-logic

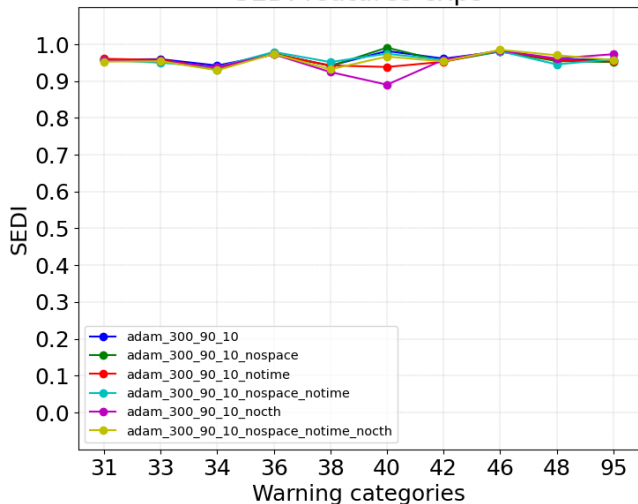
Sensitivity to ANN (MLP) setup



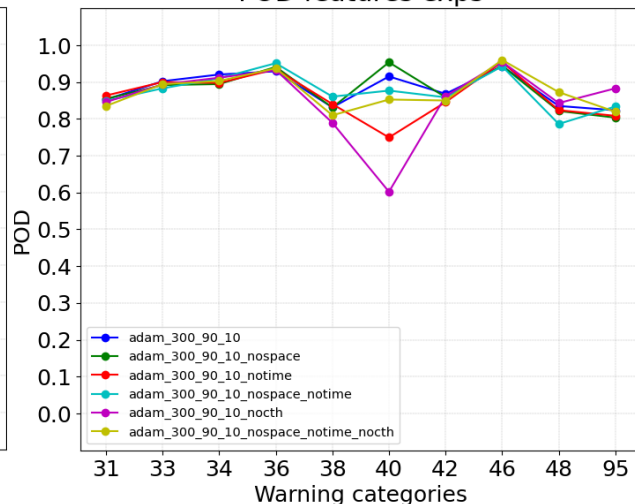
ML for emulating NCM Fuzzy-logic

Sensitivity to *feature set*

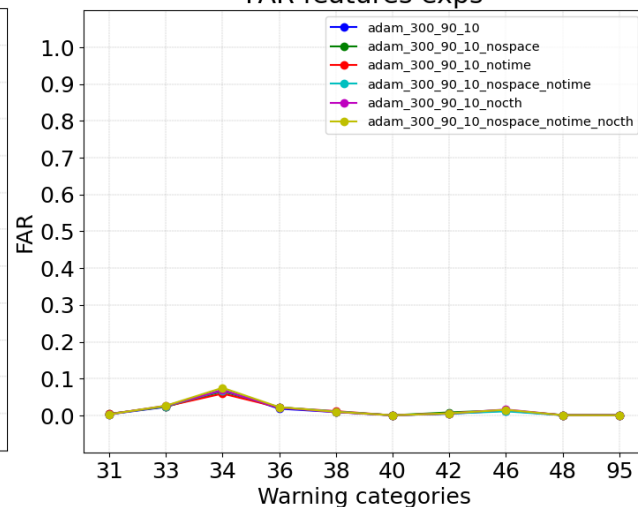
SEDI features exps



POD features exps

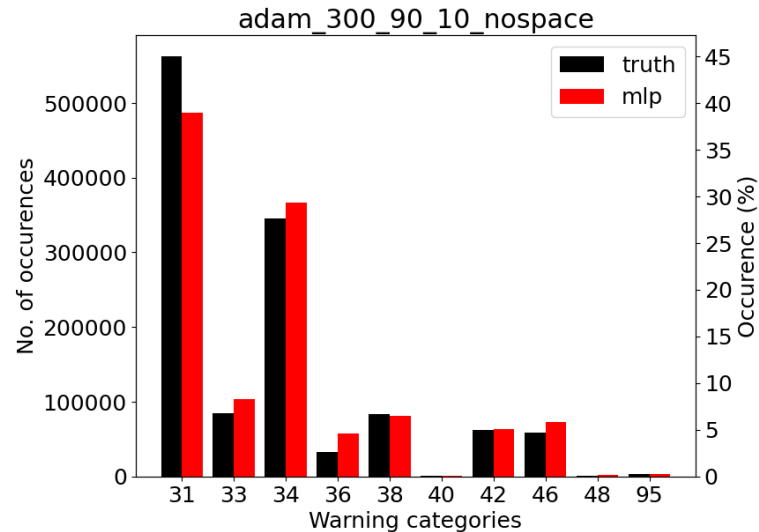
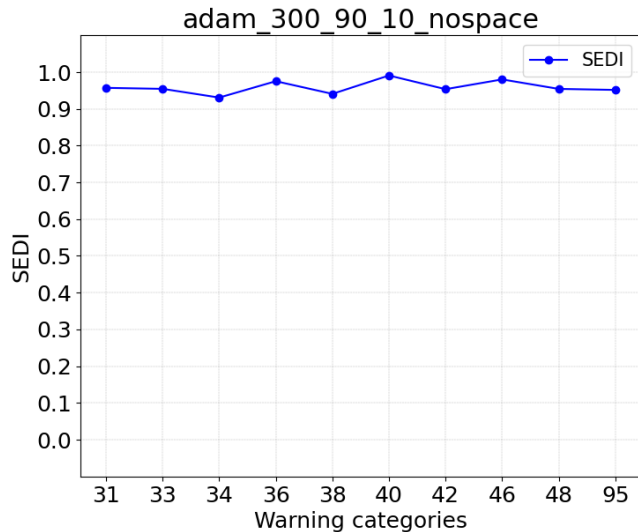


FAR features exps



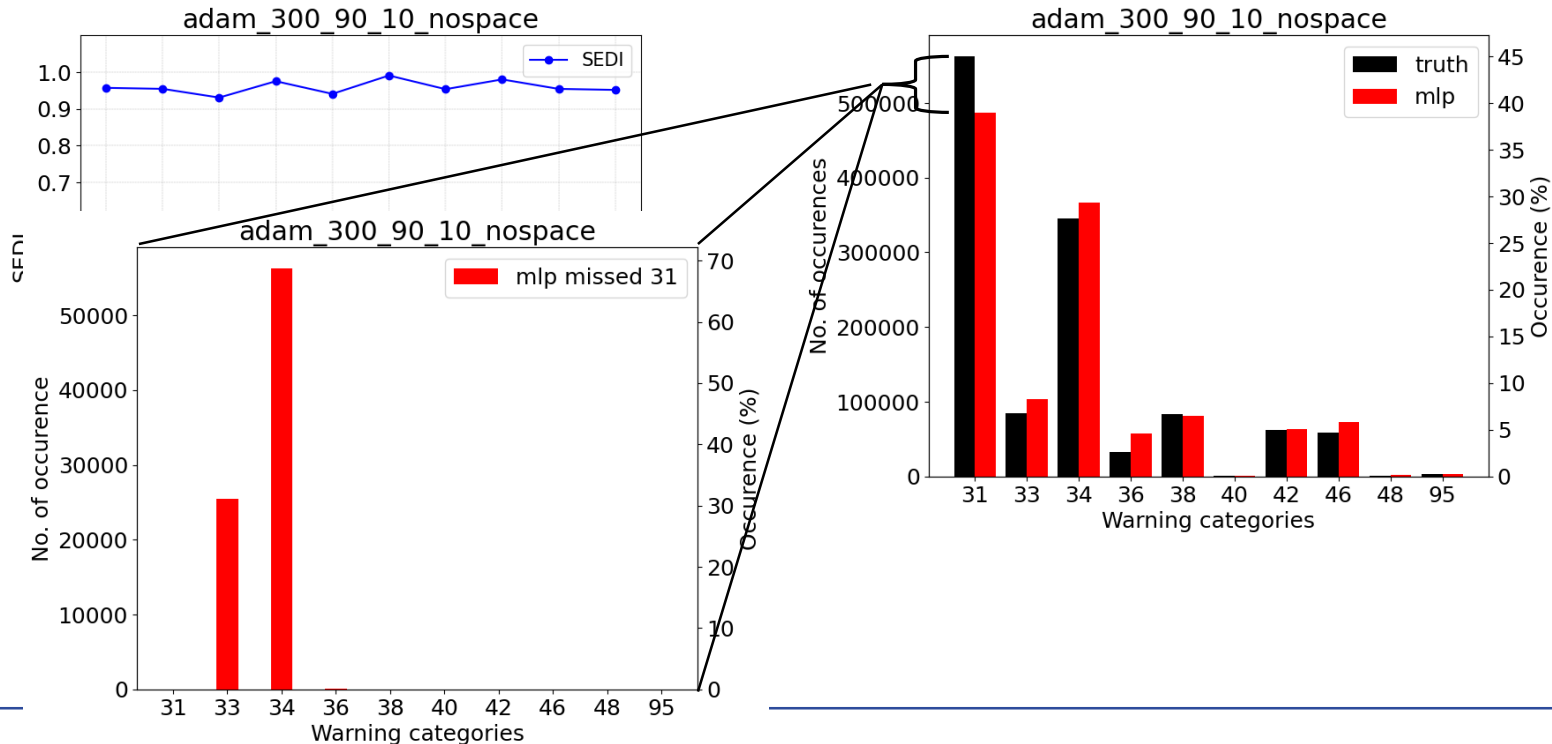
ML for emulating NCM Fuzzy-logic

So, the winner is! (solver: adam, activ. func.: relu, arch=300,90,10, alpha= 10^{-3} , etc)



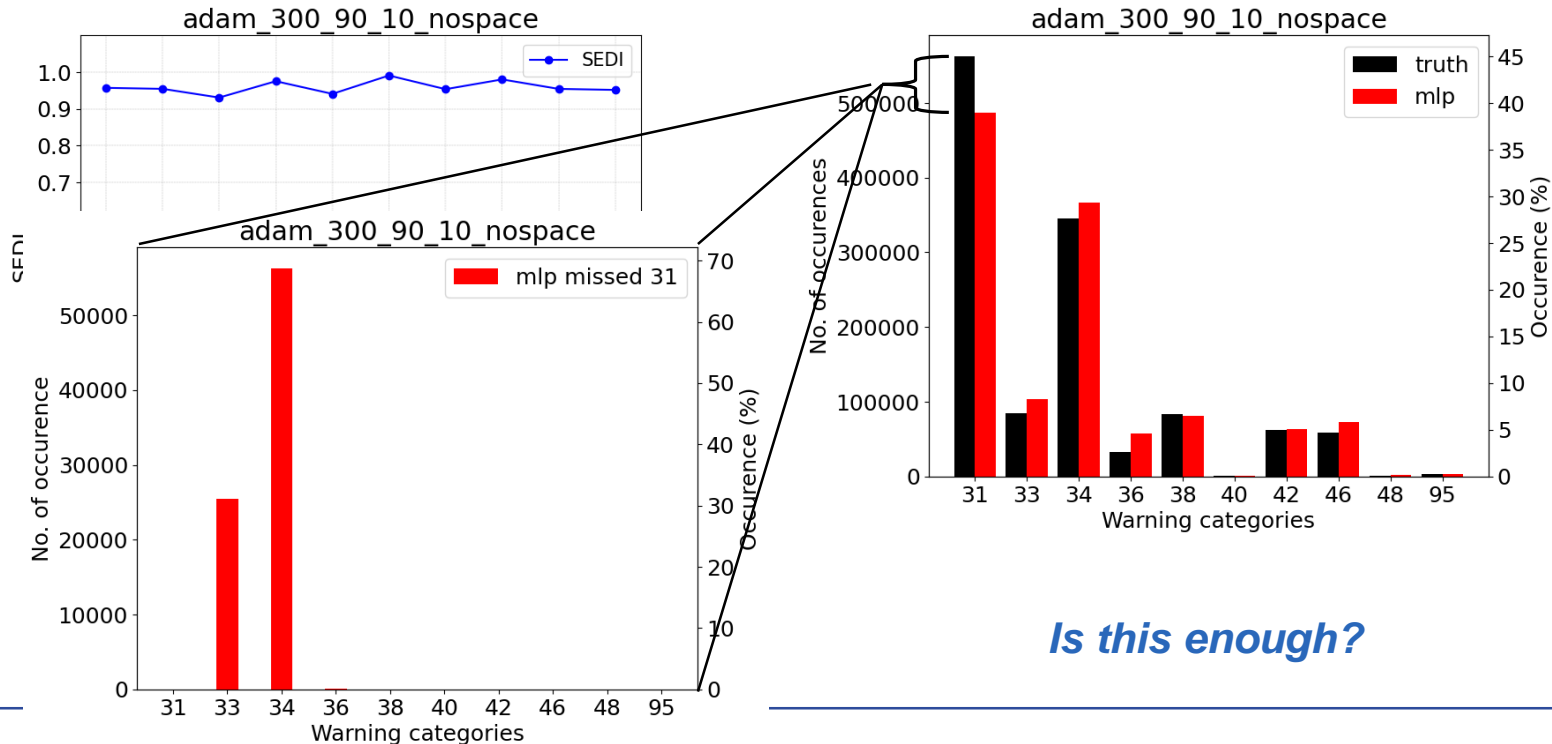
ML for emulating NCM Fuzzy-logic

So, the winner is! (solver: adam, activ. func.: relu, arch=300,90,10, alpha= 10^{-3} , etc)



ML for emulating NCM Fuzzy-logic

So, the winner is! (solver: adam, activ. func.: relu, arch=300,90,10, alpha= 10^{-3} , etc)



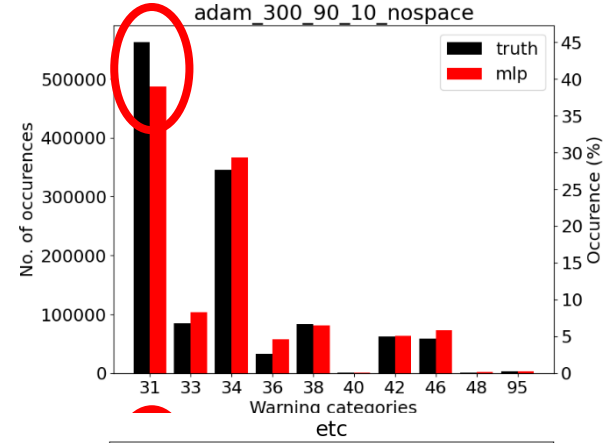
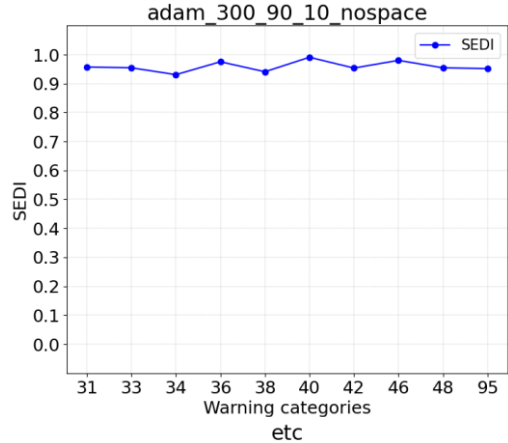
Is this enough?



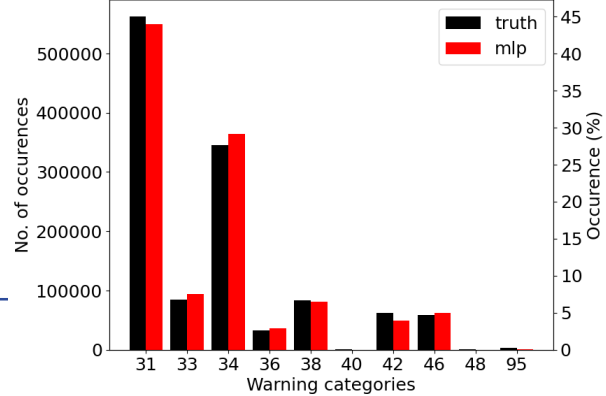
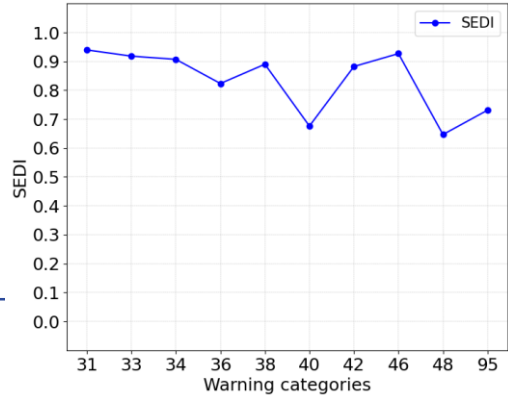
ML for emulating NCM Fuzzy-logic

SEDI vs Distribution?

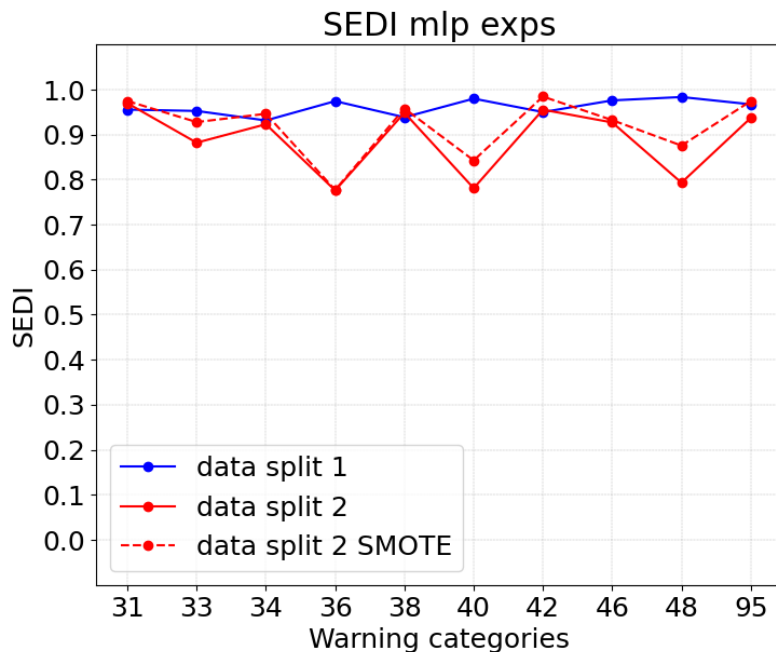
ANN



Extra Tree Classifier
(decision tree)



Not enough robust?



Reasons & solutions(?)

- Very much imbalanced data set, i.e. $f_{\text{cat40}} = 10^5 \cdot f_{\text{cat31}}$
 - Even more data needed!
 - Real data: probably not enough / expensive
 - SMOTE (Synthetic Minority Oversampling Technique) → first attempt did not help
- Optimal set-up not yet found?
 - Hyperparameter tuning

Discussion & Outlook

- To me, using an ANN still feels like a „black box“ → lot to learn!
- ANN for warning category classification:
 - not a „low-hanging fruit“ → more data needed / hyperparameter tuning
 - no real ground truth (no warning category „observations“) → fuzzy-logic best we have → no perspective to improve
 - a nice playground but not convinced about continuing
- Probably the way forward: improve forecast step
 - So far: stretching based on extrapolation by wind
 - Plan: Machine Learning (CNN, cell-based \leftrightarrow grid based?)
- PyTorch or TensorFlow (CPU & GPU) instead of Scikit-Learn (only CPU)?