Universität Augsburg
Fakultät für Angewandte Informatik

Calibrated and Uncertainty-aware Multimodal Emotion Recognition

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Bachelor thesis, 2021

Agenda

1. Uncertainty in Deep Learning (Background)
2. Predictive Uncertainty, Subjectivity and Emotion Recognition (Research Goals)
3. Obtaining Estimates of Predictive Uncertainty (Approach and Results)
4. Evaluation and Discussion (Conclusion)

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Uncertainty in Deep Learning

Introduction to Uncertainty

- Imagine a model (e.g. a neural network) which makes a **prediction** $\hat{y}$.
- But **how confident** (or the opposite uncertain) is the model about this prediction?
- Fundamental intuition:
  1. Define true uncertainty.
  2. Measure/predict uncertainty alongside with the actual prediction $\hat{y}$.
  3. Model is referred to as ***well-calibrated*** if true uncertainty matches predicted uncertainty.
- Usually true uncertainty is defined as the prediction error so **we want the models uncertainty to be high if its error (in terms of $\hat{y}$) is high**.

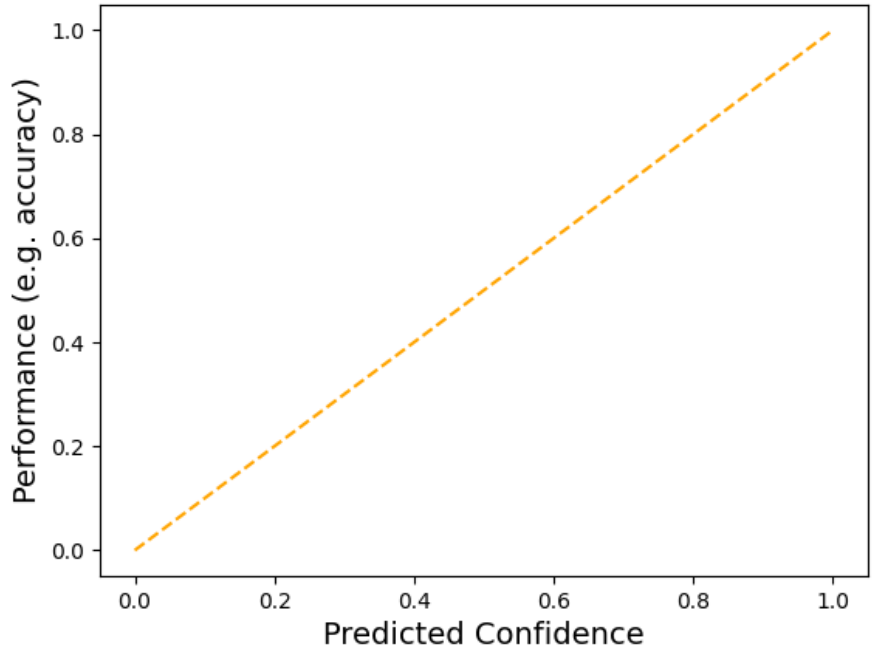

Fig.: *Well-calibrated* uncertainty measurements: the predicted confidence exactly matches the prediction error (here, represented by accuracy).

Uncertainty in Deep Learning

Types and Sources of Uncertainty

- **Aleatory** *(Data)* Uncertainty:
  - Caused by noise in the sample as it leads to non-determination of an estimation problem.
  - Imagine the landing point of an arrow.
- **Epistemic** *(Model/Knowledge)* Uncertainty:
  - Appears if the model lacks in knowledge on a sample.
  - E.g., the image of a ship, fed into a cat-vs.-dog-classifier.

Uncertainty in Deep Learning

Measuring Predictive Uncertainty

- Classification: softmax
- Bayesian modelling:
  - Obtain multiple forecasts for $\hat{y}$ (with possibly different outcomes).
  - Use the mean of them as final prediction and the **variance** among them **as measurement for uncertainty**.
  - Approaches: Monte Carlo Dropout, Ensemble Averaging, …
- Distributional parameter estimation:
  - Output parameters for probability distribution over $\hat{y}$ instead of $\hat{y}$.

Uncertainty in Deep Learning

Calibration

- Often predicted uncertainty is not well-calibrated initially.
- *(Re-) calibration*: make non well-calibrated uncertainties well-calibrated.
  1. Uncalibrated measurements of uncertainty $\hat{U}$ from a hold-out validation set.
  2. Calculate true uncertainty U of the validation set.
  3. Train a auxiliary model, the *calibrator*, to map $\hat{U}$ to U.
  4. Calibrator can be applied on uncalibrated uncertainty quantification obtained from the test set.
- Often: Isotonic Regression

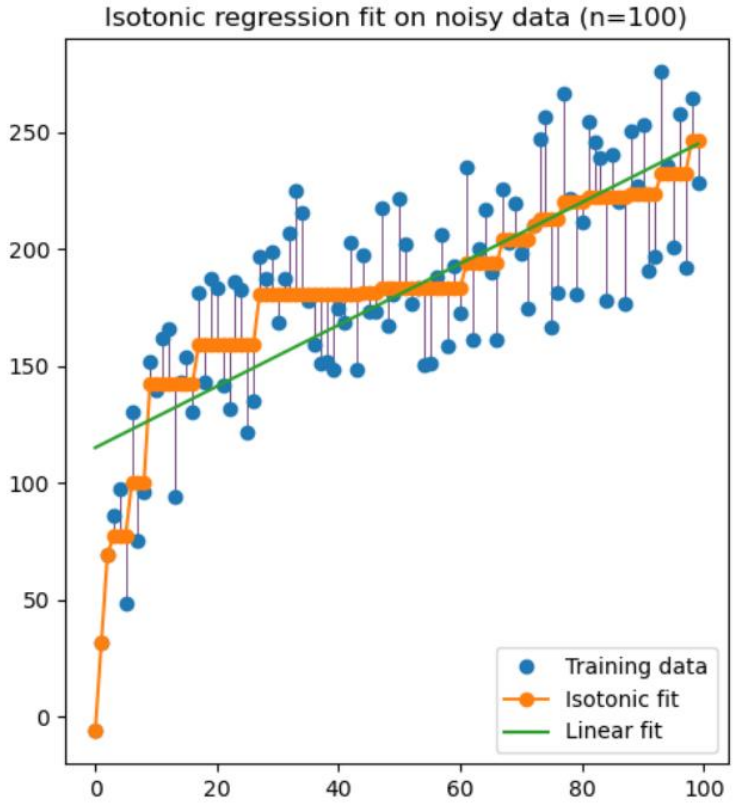

Fig.: Isotonic Regression. Image taken from: https://scikit-learn.org/stable/auto_examples/miscellaneous/plot_isotonic_regression.html

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Predictive Uncertainty, Subjectivity and Emotion Recognition

Uncertainty-aware Emotion Recognition

- Aims of this work:
  1. Measure predictive uncertainty for the task of emotion recognition.
  2. Investigate subjectivity among annotations as source of predictive uncertainty.
- **Emotion Recognition**: prediction of the emotional state, here described by valence and arousal.
- Motivation:
  - We want uncertainty to appear where the prediction error is large (common definition).
  - But why should it indeed appear there? Or, why actually is there prediction error, if it is?
  - Whether model nor anybody know the prediction error during inference. Hence, there must be underlying sources that cause it.
  - We investigate subjectivity among annotations as indicator for where we expect uncertainty.

Predictive Uncertainty, Subjectivity and Emotion Recognition

The MuSe-CaR dataset

- Contains YouTube videos of car reviews contiguously (one label per time step) annotated by valence and arousal.
- For each sample, there are available **5 annotations by different human annotators**.
- Further, there exists a gold-standard, calculated from the multiple annotations by fusion techniques.

Obtaining Estimates of Predictive Uncertainty

Research Questions

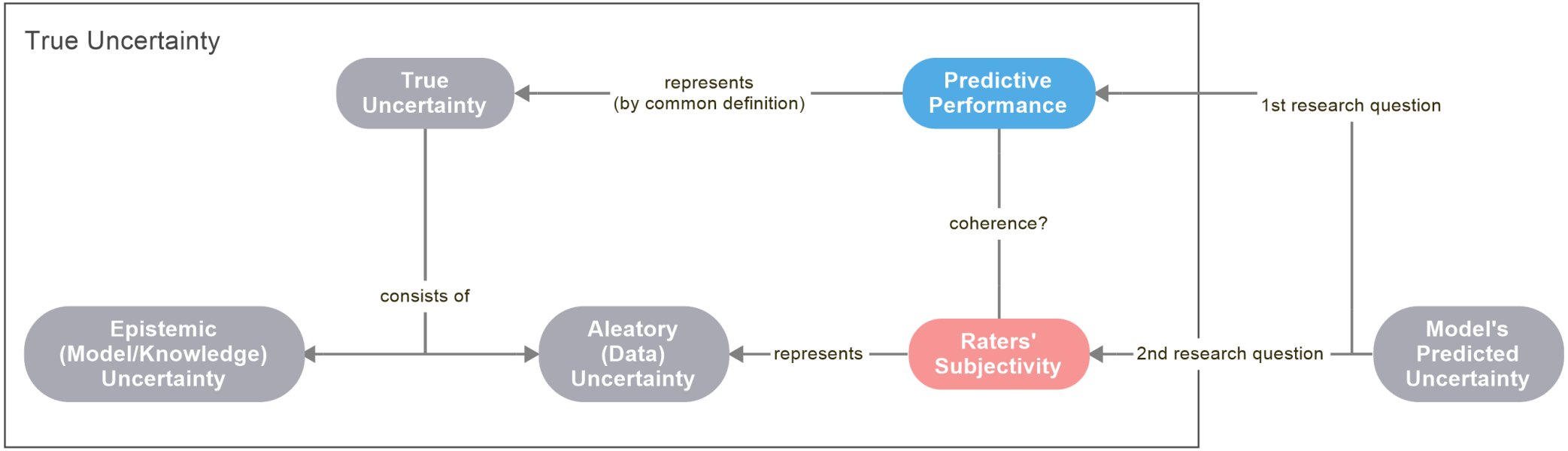

Fig.: Our research question visualized

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Obtaining Estimates of Predictive Uncertainty

Underlaying Model and Modality

- Predict either valence or arousal
- Modality and used feature sets:
  - Valence: BERT
  - Arousal: VGGish
- The model:
  - Attention → LSTM → Fully Connected

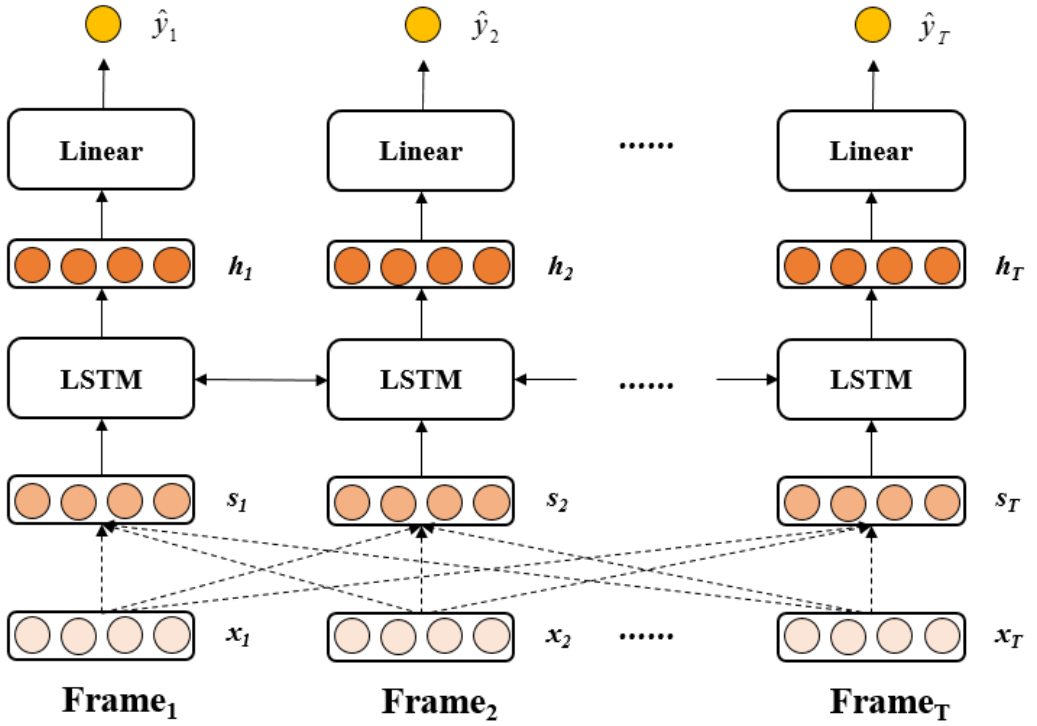

Fig.: The underlaying model, which we equipped with techniques for confidence quantification

Obtaining Estimates of Predictive Uncertainty

Before we start: Replacing Variance by Correlation

- We want to use approach like Monte Carlo Dropout to measure uncertainty, but such techniques use variance to obtain the final measurement of confidence.
- We predict steps in time of a **contiguous** emotional state.
- Each point in time t is rated based on the evaluation of the signal at t and the annotation of the latest time step $t - 1$.
- Therefore, we replace variances by correlations:
  - We obtain multiple (differing) predictions, as usual.
  - We compute the **average correlation** (PCC or CCC) **among each pair** of them.
  - The higher the correlations, the higher the model's confidence.

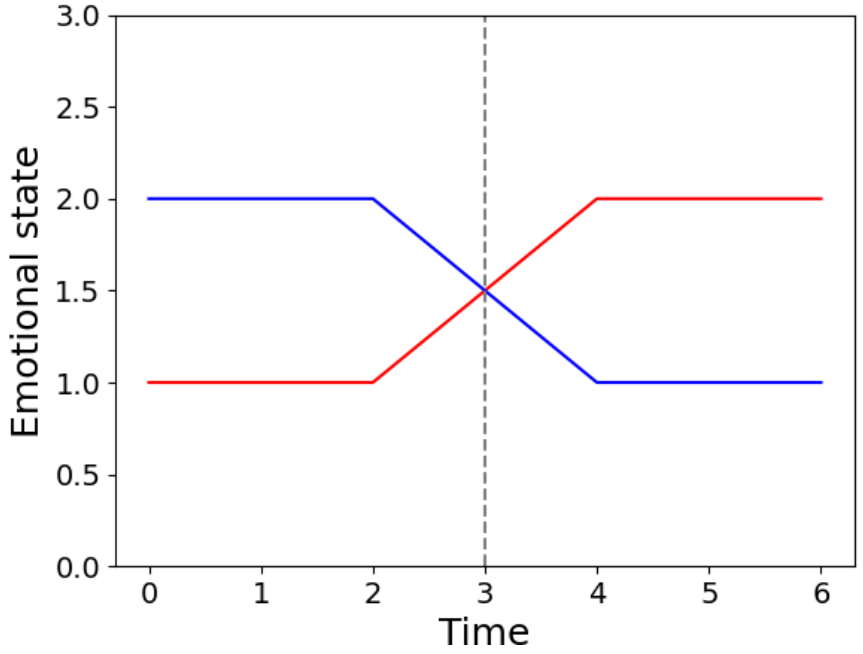

Fig.: At x = 3 both lines have the same value. But when it comes to measuring the disagreement of them, the correlation at this point is much more expressive, especially because the shown values at each time step come from one contiguous measurement. Each point in time is not a standalone prediction.

Obtaining Estimates of Predictive Uncertainty

Overview over Concepts

- Two main conceptional approaches:
  - Local uncertainty quantification: for now, anything happens **per time step**, or *locally*.
  - Global uncertainty quantification: measurements are done for **multiple time steps** (sub-samples, respectively) **together**, or *globally*.

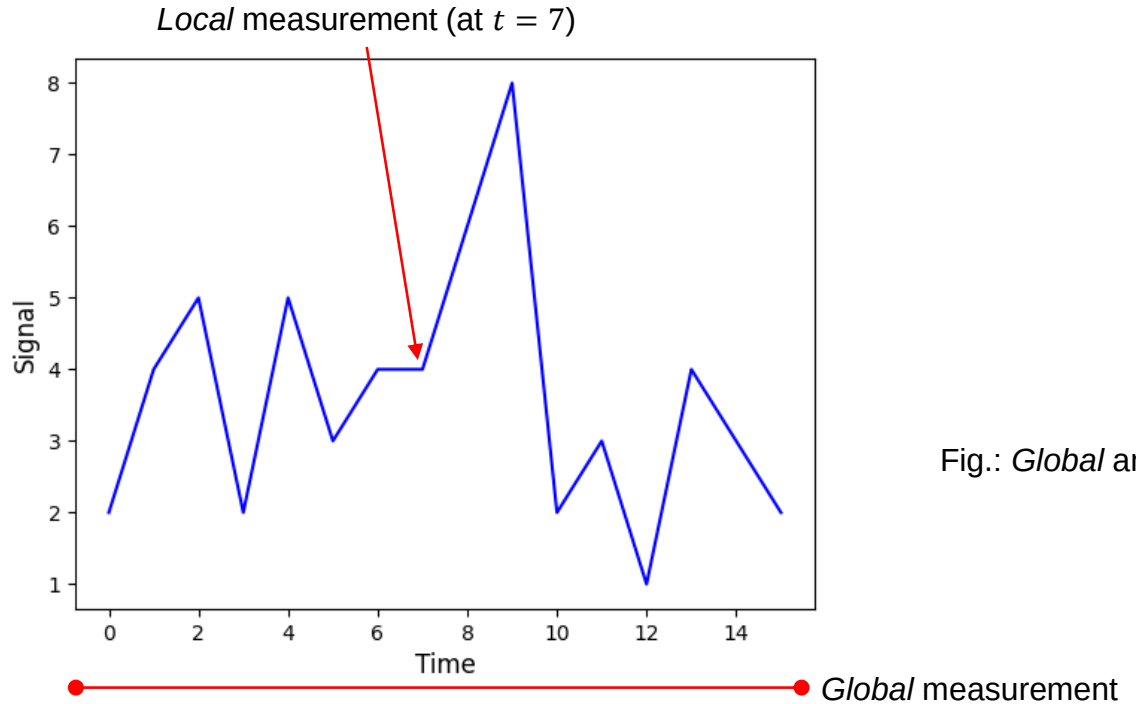

Fig.: *Global* and *local* measurements

Obtaining Estimates of Predictive Uncertainty

Local Uncertainty Quantification: Definitions of True Uncertainty

Predictive Performance

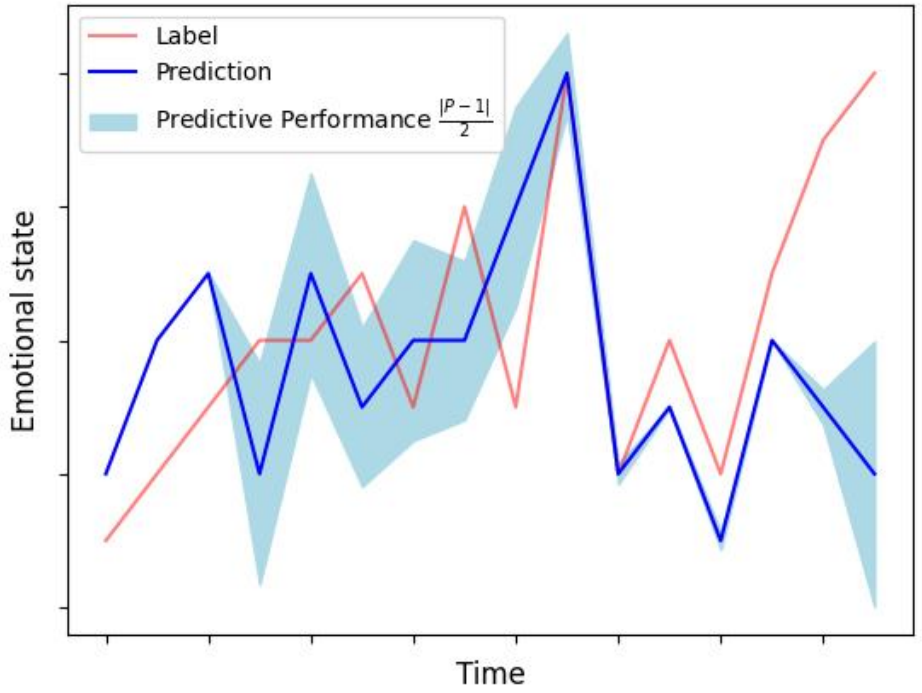

Fig.: Predictive Performance of a predictions in terms of the label

Subjectivity among raters

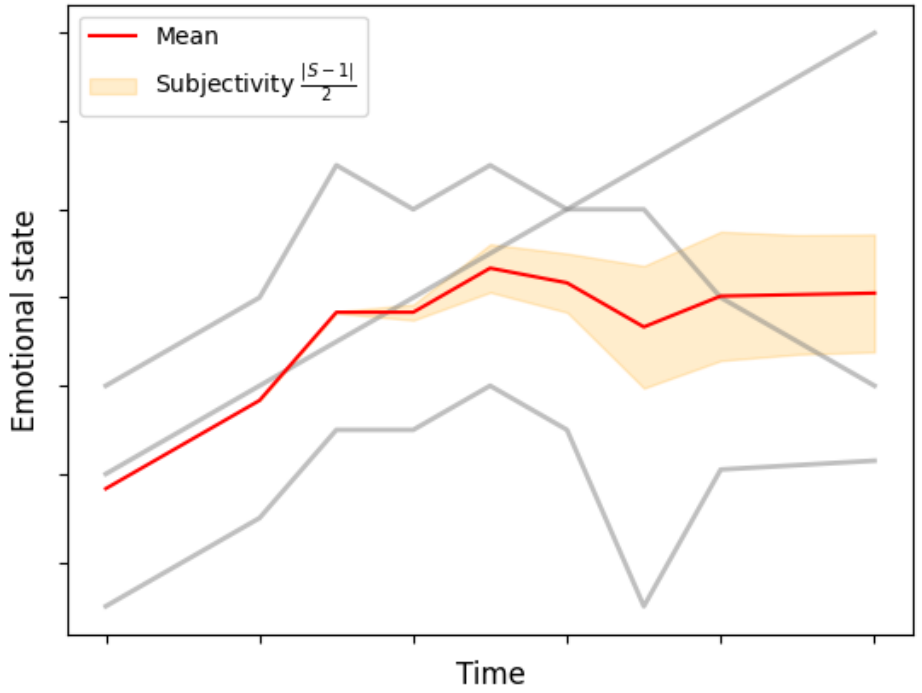

Fig.: Subjectivity among multiple (gray) raters

Obtaining Estimates of Predictive Uncertainty

Local Uncertainty Quantification: Definitions of Predicted Uncertainty

- Monte Carlo Dropout
- Proposing *tilted CCC (tCCC)*:
  - Mid node: usual CCC loss criterion
  - Outer nodes: RCE_3 and RCE_{10} as criterion (n: sample length).

$$RCE_w(\hat{y}) = \frac{1}{n}\sum_{j=w}^{n}(1 - PCC(\hat{y}_{j-w+1} \dots \hat{y}_j, y_{j-w+1} \dots y_j))$$

  - Creates mini-ensemble with 2 nodes, focusing on different errors.

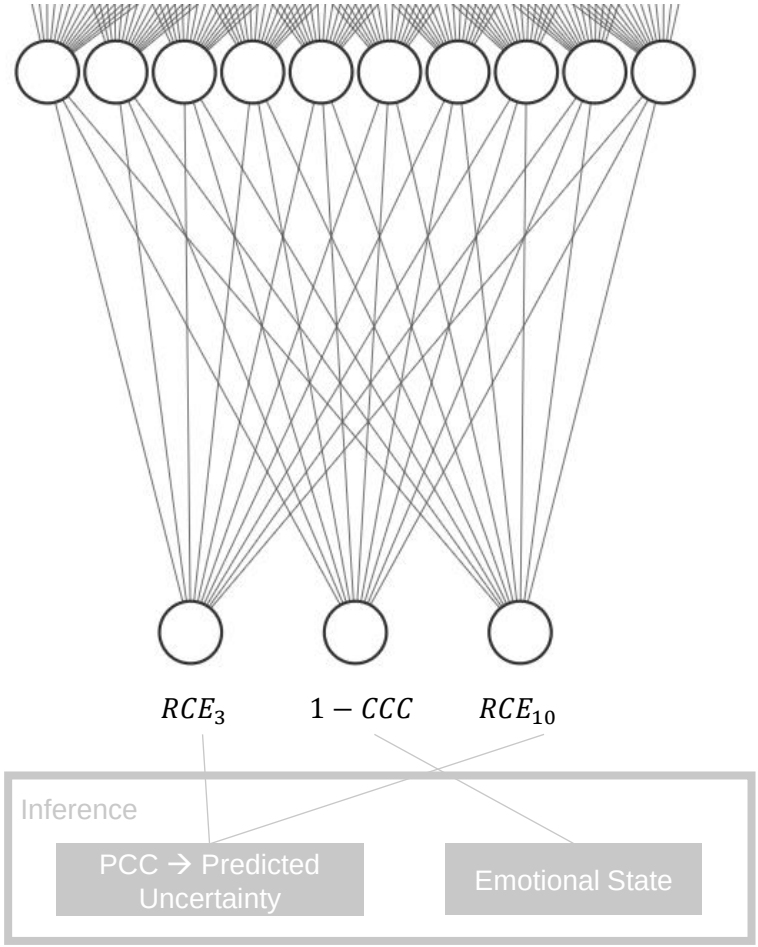

Fig.: Losses and inference of tCCC visualized

Obtaining Estimates of Predictive Uncertainty

Local Uncertainty Quantification: Results

- Quantified uncertainty did not match true uncertainty, whether subjectivity nor predictive performance.
- Conceptional issue:
  - Monte Carlo Dropout: model optimized using CCC loss → evaluates the complete sample, not per time step.
  - During training with tCCC, the outer nodes did not converge significantly.
  - → Emotion recognition (here) works more globally → model is capable to predict longer trends of the emotion state, but not locally.
  - Makes sense: human labeller's reaction time >> 3 timesteps (0,75 sec.)
  - **If the model's (local) forecasts are prone to be wrong, so meaningless, they naturally lead to non-reliable confidence estimates.**

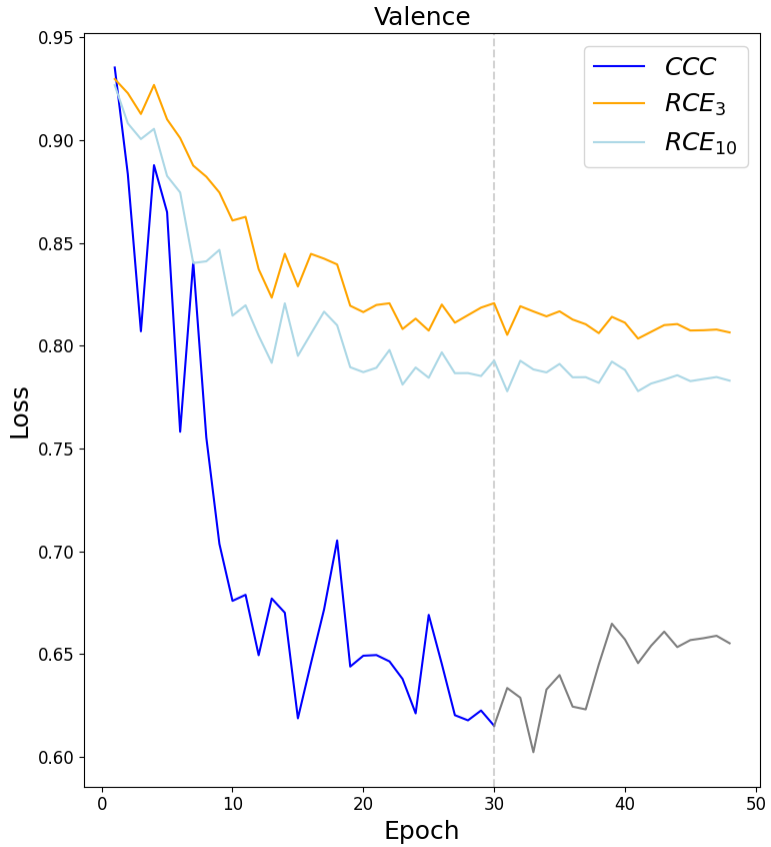

Fig.: tCCC node convergence

Obtaining Estimates of Predictive Uncertainty

Global Uncertainty Quantification: Definitions

- Instead of measuring one value for uncertainty per time step, we now define uncertainty for complete samples.
- As we expect uncertainty to vary over time, we split up samples into non-overlapping sub-samples of length 20 (5 seconds).

True Uncertainty (for one sub-sample)

- Predictive Performance

$$P = CCC(y, \hat{y})$$

  - With label y and prediction $\hat{y}$.
- Subjectivity among raters

$$S = \frac{1}{10} \sum_{i=1}^{5} \sum_{k=i+1}^{5} CCC(x_i, x_k)$$

  - With x_i, the annotation of the i-th rater.

Predicted Uncertainty (for one sub-sample)

- Monte Carlo Dropout
- Ensemble Averaging
- → Correlation among differing prediction as measurement for model's confidence.

Obtaining Estimates of Predictive Uncertainty

Global Uncertainty Quantification: Results

True Uncertainty	Emotional Dimension	Method	CCC devel / test [uncalibrated]	CCC devel / test [Isotonic Regression]
Predictive Performance	Valence	Ensemble Averaging	**0,18 / 0,27**	0,13 / 0,16
		Monte Carlo Dropout	0,18 / 0,24	0,16 / 0,17
	Arousal	Ensemble Averaging	**0,23 / 0,12**	0,22 / 0,11
		Monte Carlo Dropout	0,20 / 0,05	0,27 / 0,08
Raters' Subjectivity	Valence	Ensemble Averaging	0,03 / 0,04	0,02 / 0,03
		Monte Carlo Dropout	0,03 / 0,04	0,02 / 0,03
	Arousal	Ensemble Averaging	0,08 / 0,04	**0,13 / 0,06**
		Monte Carlo Dropout	0,04 / 0,01	0,06 / 0,02

Verification: Predictive Performance and subjectivity correlate.

Obtaining Estimates of Predictive Uncertainty

Global Uncertainty Quantification: Results

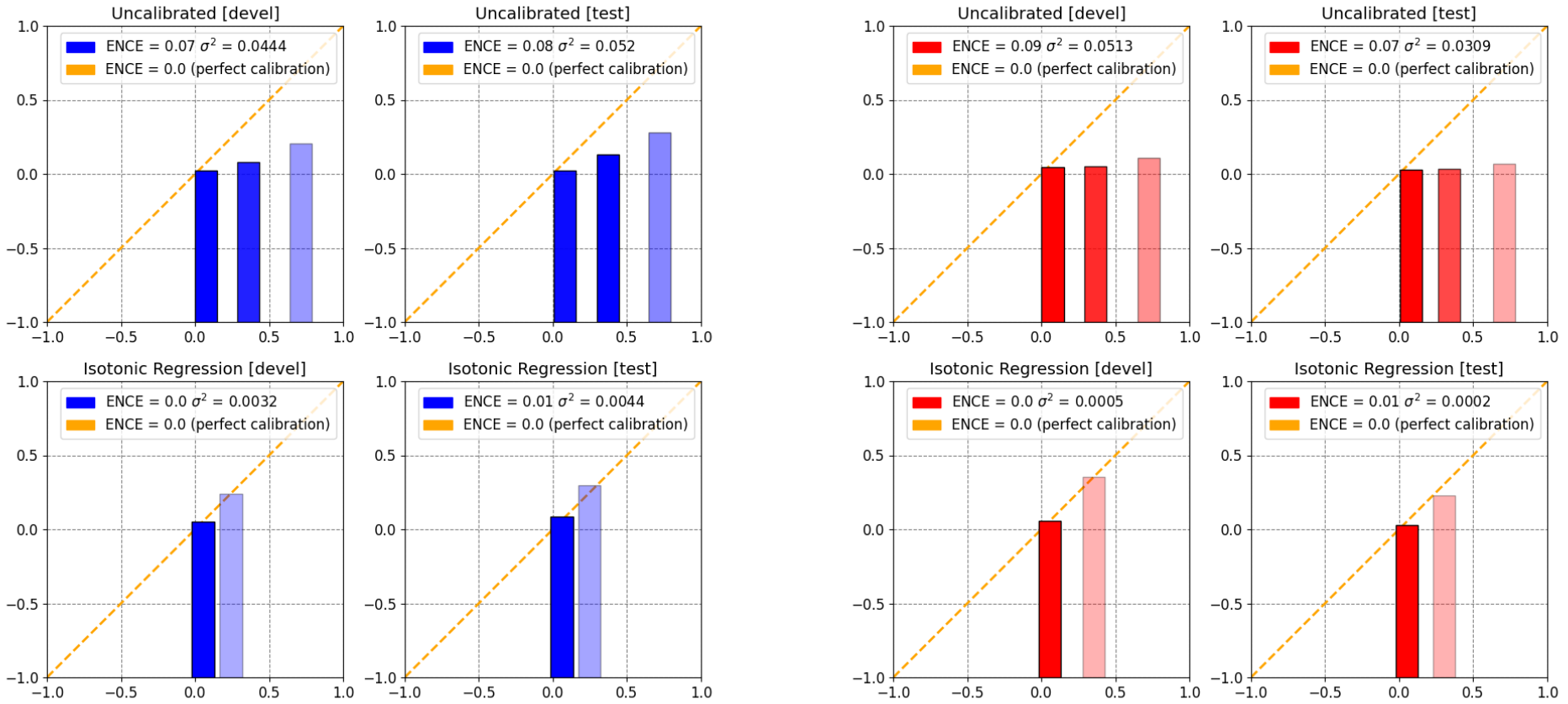

Fig.: Some results visualized with Reliability Diagrams. Predictive Performance as true confidence with Ensemble Averaging for valence (left) and Subjectivity as true confidence with Ensemble Averaging for arousal (right). As more transparent a bin, the less (sub-) samples fall into it.

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Evaluation and Discussion

Summary

- We proposed techniques to transfer the procedure of uncertainty quantification to contiguous forecasting, by replacing variance with correlations.
- We extended the measurement of true uncertainty, which is used to judge quality of predicted uncertainty, by another approach: we defined subjectivity among multiple (human) raters as additional comparative value for a model's confidence, next to the predictive performance of the model.
- Initial assumption: $Prediction\ Error \sim^{(1)} Predicted\ Uncertainty \sim^{(2)} Raters'subjectivity$
- As experiments in local uncertainty failed because of conceptional issues, we restrict further thoughts on global uncertainty measurements.

Evaluation and Discussion

Conclusion: first research question

- Observed coherence between predictive performance and predicted uncertainty.
- The correlation of about 0.2
  - Predictive performance unites each source of uncertainty
  - No matter what underlying reasons cause the model's uncertainty, they should reflect on its predictive performance → correlation too weak?!
- **Uncertainty isn't an explicit forecast → implicit measurement → anything better than approximation would be weird.**

Evaluation and Discussion

Conclusion: second research question

- As for the coherence between subjectivity among annotations and predicted uncertainty, it is, if at all, barely available.
- Subjectivity is only one source of uncertainty, among others.
- Subjectivity among raters indicates a noisy sample (as features did not transport an unambiguous signal), so aleatory uncertainty.
- So, what about epistemic uncertainty?
- Epistemic uncertainty is caused by lacks knowledge from the model about the fed in data, which is not contained in raters' subjectivity.
- The weaker correlations between subjectivity among annotations and predicted uncertainty, than those between predictive performance and predicted uncertainty, might be explained by the disregard of epistemic uncertainty in this definition of true uncertainty.

Evaluation and Discussion

Future Work

1. Vary the length of sub-samples (not just 20)
   - First experiments with lengths 10 and 50 do **not** indicate a significant improvement.
2. Use advances fusion technique to obtain final prediction from Monte Carlo Dropout and Ensemble Averaging:
   - This would reflect on predictive performance and make it, as a definition of true confidence, more reliable.
3. Epistemic Uncertainty:
   - Furthermore, we could think about manually quantifying the lack of knowledge for a sub-sample and use this as a definition for true uncertainty, as we did with subjectivity among annotations.

Evaluation and Discussion

Raters‘ subjectivity is independent of the feature set!

Future Work: Incorporating Epistemic Uncertainty

- Simpler feature embeddings (valence on fastText, instead of BERT): try to observe, if this increases predicted uncertainty and decreases the proportion of aleatory uncertainty relative to the overall uncertainty.
- Less expressive features → expect **larger general model’s uncertainty** and relatively more epistemic uncertainty, so **relatively less aleatory uncertainty**, as overall uncertainty decomposes into aleatory and epistemic uncertainty.

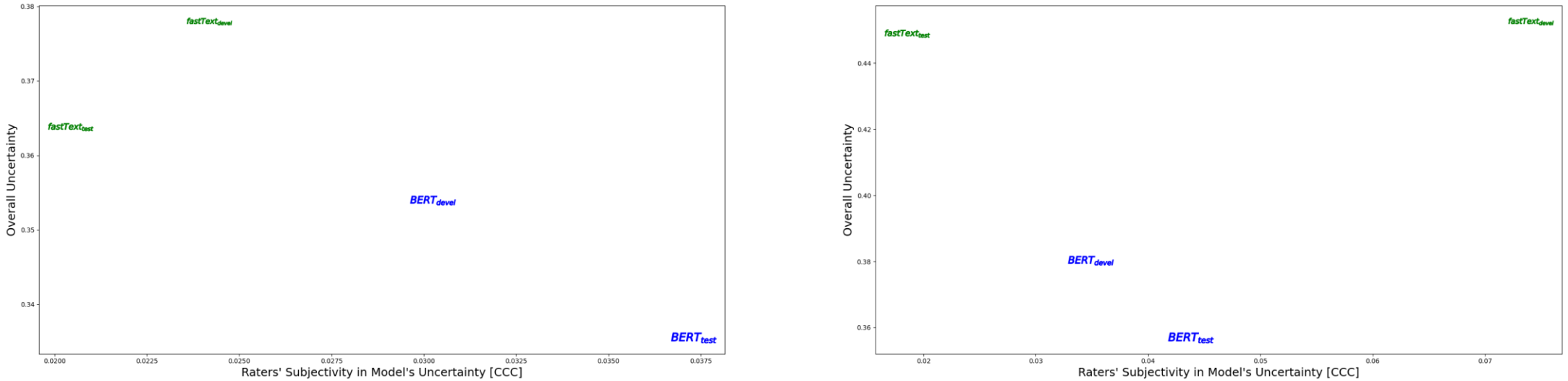

Fig.: Comparing predicted uncertainty with different features (left: Monte Carlo Dropout, right: Ensemble Averaging).

Thank you for your attention!

Any questions?

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Backlog

Obtaining Estimates of Predictive Uncertainty

Local Uncertainty Quantification: Formalization

True Uncertainty (at time step j)

- Predictive Performance (left figure)

$$P_j = PCC(y_{j-t} \dots y_j, \hat{y}_{j-t} \dots \hat{y}_j) \; with \; t = 2$$

  - With the prediction for the emotion $\hat{y}_i$ and the label y.

- Subjectivity among raters (right figure)

$$S_j = \frac{1}{10} \sum_{i=1}^{5} \sum_{k=i+1}^{5} PCC(x_{i,j-t} \dots x_{i,j}, x_{k,j-t} \dots x_{k,j-t}) \; with \; t = 2$$

  - With x_i, the annotation of the i-th rater.

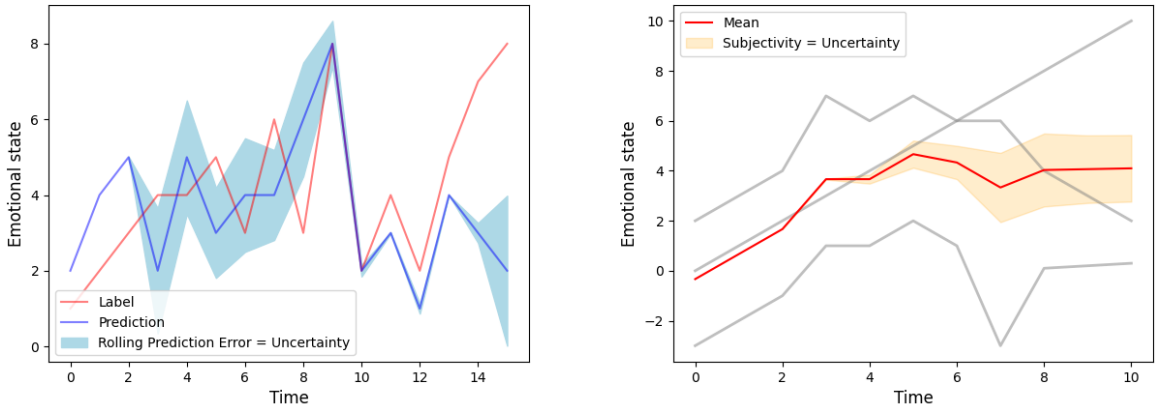

Fig.: Predictive Performance (left) and subjectivity among raters (right).

Predicted Uncertainty (at time step j)

- Monte Carlo Dropout

$$MCD_j = \frac{1}{10} \sum_{i=1}^{5} \sum_{k=i+1}^{5} PCC(\hat{y}_{i,j-t} \dots \hat{y}_{i,j}, \hat{y}_{i,k-t} \dots \hat{y}_{k,j}) \; with \; t = 2$$

  - With the model's i-th prediction for the emotional state $\hat{y}_i$.

- Proposing *tilted* CCC (tCCC)
  - Network has three output nodes:
    - Mid node: usual CCC loss criterion (used for inference of emotional state).
    - Outer nodes: RCE_3 and RCE_{10} as criterion (n: sample length).

$$RCE_w(\hat{y}) = \frac{1}{n} \sum_{j=w}^{n} (1 - PCC(\hat{y}_{j-w+1} \dots \hat{y}_j, y_{j-w+1} \dots y_j))$$

    - Creates mini-ensemble with 2 nodes, focusing on different errors (rolling correlation error over the 3 and 10 latest time steps, respectively).
    - Used to obtain uncertainty quantification, by computing correlation between them (similar to P_j).

Obtaining Estimates of Predictive Uncertainty

Global Uncertainty Quantification: Formalization

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Predicted Uncertainty (for one sub-sample)

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  - With the model's i-th prediction for the emotional state $\hat{y}_i$.

- Ensemble Averaging
  - Exact the same, as Monte Carlo Dropout, only with forecasts $\hat{y}_i$ from five different models/seeds, instead of five forward runs.

Correlation Metrics

- Pearson Correlation Coefficient (PCC):

$$PCC(x,y) = \frac{Cov(x,y)}{\sqrt{\sigma^2(x)}\sqrt{\sigma^2(y)}}$$

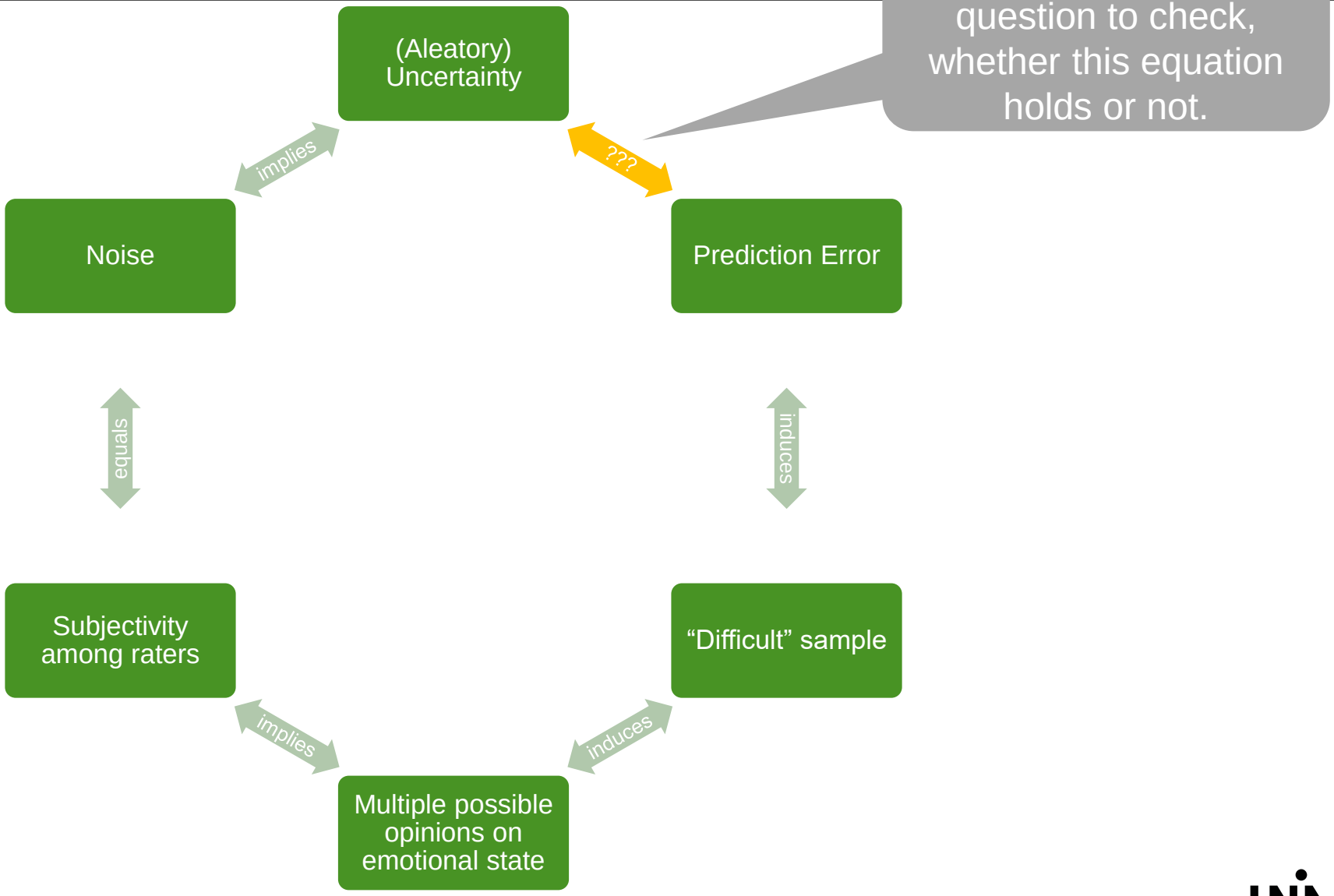
- Concordance Correlation Coefficient (CCC):

$$CCC(x,y) = \frac{2Cov(x,y)}{\sigma^2(x) + \sigma^2(y) + (\mu(x) - \mu(y))^2}$$

Notation: the mean μ, variance σ^2 and $Cov(x,y) = \frac{1}{n}\sum_{i=1}^{n}(x_i - \mu(x))(y_i - \mu(y))$

Both are limited to [-1,1] with -1 indicating total negative correlation and +1 perfect correlation.

Research Questions



tCCC Node Convergence