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Submission 22	
Title:	NP-PROV: Neural Processes with Position-Relevant-Only Variances
Paper:	(Jun 18, 13:44 GMT)
Author keywords:	Neural Processes Uncertainty evaluation Position-Relevant-Only Variance
EasyChair keyphrases:	neural process (333), relevant only variance (190), self correlation (180), context data (140), function value (140), position relevant (130), latent variable (120), context point (110), cross correlation (100), target point (100), target data (90), gaussian process (90), grid dataset (80), smart meter (80), neural network (80), conv2d conv2d conv2d (79), log likelihood (70), linear linear (60), convolutional conditional neural process (60), training range (60), mean function (60), covariance function (50), high self correlation (47), attentive neural process (47), conditional neural process (47), gp sampled dataset (47), whole image (40), grid scenario (40), posterior distribution (40), model structure (40)
Abstract:	Neural Processes (NPs) families encode distributions over functions to a latent representation, given context data, and decode posterior mean and variance at unknown locations. Since mean and variance are derived from the same latent space, they may fail on out-of-domain tasks where fluctuations in function values amplify the model uncertainty. We present a new member named Neural Processes with Position-Relevant-Only Variances (NP-PROV). NP-PROV hypothesizes that a target point close to a context point has small uncertainty, regardless of the function value at that position. The resulting approach derives mean and variance from a function-value-related space and a position-related-only latent space separately. Our evaluation on synthetic and real-world datasets reveals that NP-PROV can achieve state-of-the-art likelihood while retaining a bounded variance when drifts exist in the function value.
Submitted:	Jun 06, 22:38 GMT
Last update:	Jun 15, 03:15 GMT

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Reviews

Review 1

Overall evaluation:

-2: (reject)
From a technical viewpoint the submitted paper seems sound. However, the authors have uploaded a paper version in ArXiv (https://arxiv.org/abs/2007.00767v1), which itself cancels out the strict double-blind review policy ("All submitted papers MUST be anonymous") of WISE.

Review 2

Overall evaluation:

2: (accept)
The paper proposed a new member of Neural Processes, NP-PROV, that derives its variances from a position-relevant only variable. It is claimed to provide robust uncertainty evaluation under value shifts. In order to match better with the original Gaussian Process, a self-correlation auto-encoder is added to the method. NP-PROV is validated on extensive 1D and 2D experiments, including a challenging few shot image regression task, the results manifest the outperformance and the effectiveness under data fluctuations.

Strength:
1. Novelty of the position-relevant-only variance idea.
2. Extensive datasets validation and outstanding performance.

Weakness:
1. Insufficient clarification on the motivation.
2. Missing metrics for evaluating out-of-domain predictions.

Comments:
1. In the abstract, the concepts of “function value” and “position” need further clarification.
2. In the introduction, before claiming the major contributions, why location-related variance can tackle functional value shift needs elaboration.
3. Contribution claim in the introduction, the motivation for self-correlation modules needs explanation in the previous context.
4. Section 2 Background Convolutional Conditional Neural Processes, if it has already addressed the out-of-range prediction, what type of out-of-domain predictions is NP-PROV targeting?
5. First paragraph of Section 4 Experiments, a typo: “few-shot regression tasks”.
6. In table I, it seems that Log-likelihood is no longer a descent metric to evaluate the method under shifts (the last two rows) considering the large-scale difference. Maybe worth introducing a new metric.
7. The major discovery of the method needs to be crystalized in the conclusions.

Review 3

Overall evaluation:	**0**: (borderline paper) In the paper titled "NP-PROV: Neural Processes with Position-Relevant-Only Variances " authors developed and designed a new Neural Processing member that considers position-relevant variances. While the research aim is very exciting and challenging, it would have been great if authors provided proofs of all the mathematical claims they have mentioned in the paper. For example, on page 4 authors mentioned "The first layer maps X to a uniformly discretized grid space Xt = [x1, ..., xt]⊤ built on the lower and upper range of X ∪ X⋆. The second layer maps the space back to X⋆" without any proof. Likewise, authors introduced lots of mathematics with an assumption that prospective readers can proof these. Authors made the paper very complex without any reason. It is suggested that authors should prepare a manuscript so that prospective readers can easily implement the underlying theory. The paper should be re-written substantially so that the contribution to the paper becomes transparent. Moreover, the results section should be explained more to reflect how the proposed model outperforms the traditional model if the new Neural Processing member is used in the CNN structure.