**### Task 1 ###**

**Source Documents:**

Link to OpenReview: <https://openreview.net/forum?id=HygXkJHtvB>

**Meta-review:**

There has been significant discussion in the literature on the effect of the properties of the curvature of minima on generalization in deep learning. This paper aims to shed some light on that discussion through the lens of theoretical analysis and the use of a Bayesian Jeffrey's prior. It seems clear that the reviewers appreciated the work and found the analysis insightful. However, a major issue cited by the reviewers is a lack of compelling empirical evidence that the claims of the paper are true. The authors run experiments on very small networks and reviewers felt that the results of these experiments were unlikely to extrapolate to large scale modern models and problems. One reviewer was concerned about the quality of the exposition in terms of the writing and language and care in terminology. Unfortunately, this paper falls below the bar for acceptance, but it seems likely that stronger empirical results and a careful treatment of the writing would make this a much stronger paper for future submission.

**### Task 2 ###**

**Source Documents:**

Link to OpenReview: <https://openreview.net/forum?id=s_mEE4xOU-m>

**Meta-review:**

The paper received an uniformly positive evaluation, although all the scores are in the \"borderline / weak accept\" range. The authors included a long and comprehensive rebuttal and actively participated in the discussion, which made some of the reviewers updating their scores.\n\nI recommend the paper to be accepted, but I understand the decision could be reverted when comparing the paper with the other candidates.

**### Task 3 ###**

**Source Documents:**

Link to OpenReview: <https://openreview.net/forum?id=Byx9p2EtDH>

**Meta-review:**

The paper considers the case where policies have been learned in several environments - differing only according to their transition functions. The goal is to achieve a policy for another environment on the top of the former policies. The approach is based on learning a state-dependent combination (aggregation) of the former policies, together with a \"residual policy\". On the top of the aggregated + residual policies is defined a Gaussian distribution. The approach is validated in six OpenAI Gym environments. Lesion studies show that both the aggregation of several policies (the more the better, except for the computational cost) and the residual policy are beneficial. \n\nQuite a few additional experiments have been conducted during the rebuttal period according to the reviewers' demands (impact of the quality of the initial policies; comparing to fine-tuning an existing source policy).\n\nA key issue raised in the discussion concerns the difference between the sources and the target environment. It is understood that \"even a small difference in the dynamics\" can call for significantly different policies. Still, the point of bridging the reality gap seems to be not as close as the authors think, for training the aggregation and residual modules requires hundreds of thousands of time steps - which is an issue in real-world robotics.\n\nI encourage the authors to pursue this promising line of research; the paper would be definitely very strong with a proof of concept on the sim-to-real transfer task.

**### Task 4 ###**

**Source Documents:**

Link to OpenReview: <https://openreview.net/forum?id=rkl_f6EFPS>

**Meta-review:**

This paper focuses on the problem of robustness in the network with random loss of neurons. However, reviewers had issues with insufficient clarity of the presentation, and lack of discussion about closely related dropout approach.\n\n \n

**### Task 5 ###**

**Source Documents:**

Link to OpenReview: <https://openreview.net/forum?id=F0DowhX7_x>

**Meta-review:**

This work proposes using structured energy networks as loss functions for training feed forward networks to solve structured prediction tasks. The reviewers find the paper to be well written and easy to follow. The contribution is well positioned with respect to the literature and empirical results are strong. During the discussion period the authors addressed the concerns of the most negative reviewer sufficiently for them to increase their score. I can therefore recommend accepting this paper.

**### Task 6 ###**

**Source Documents:**

Link to OpenReview: <https://openreview.net/forum?id=dMK7EwoTYp>

**Meta-review:**

There was a range of reactions to this paper from borderline reject to strong accept. Although several of the reviewers highlighted that the contribution could be viewed as incremental, it is clearly described, and robust across different types of scenes, and I concur with the three reviewers that give positive ratings. Therefore I am accepting this paper.