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## Minicorpus de Abstracts

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### 1. Minicorpus

#### 1.1 Setting

##### Argue about the topics prominence

**The theory of** reinforcement learning **provides a normative account, deeply rooted in** psychological and neuroscientific perspectives on animal behaviour, of how agents may optimize their control of an environment.

**Tags:** *introduce*

Recurrent neural networks (RNNs) **are a powerful model for** sequential data.

**Tags:** *describe*

Topic models, such as latent Dirichlet allocation (LDA), **can be useful tools for the statistical analysis of** document collections and other discrete data.

**Tags:** *describe*

Recurrent neural networks (RNNs) **stand at the forefront of many recent developments in** deep learning.

**Tags:** *compare*

In many multivariate domains, **we are interested in** analyzing the dependency structure of the underlying distribution, e.g., whether two variables are in direct interaction.

**Tags:** *introduce*

**Estimating** influence on social media networks **is an important practical and theoretical problem (...)**

**Tags:** *introduce*

Inductive transfer learning **has greatly impacted** computer vision (...)

**Tags:** *introduce*

Adversarial examples **pose security concerns because** they could be used to perform an attack on machine learning systems, even if the adversary has no access to the underlying model.

**Tags:** *introduce*

### **Familiarize terms, objects, or processes**

End-to-end training **methods such as** Connectionist Temporal Classification **make it possible to** train RNNs for sequence labelling problems where the input-output alignment is unknown.

**Tags:** *describe*

The LDA **model assumes that** the words of each document arise from a mixture of topics, **each of which is** a distribution over the vocabulary.

**Tags:** *describe*

**We can represent** dependency structures using Bayesian network models. To analyze a given data set, Bayesian model selection **attempts to find** the most likely (MAP) model, and uses its structure to answer these questions.

**Tags:** *describe*

Skin cancer, the most common human malignancy, is primarily diagnosed visually, **beginning with an** initial clinical screening **and followed potentially by** dermoscopic analysis, a biopsy and histopathological examination.

**Tags:** *enumerate*

An adversarial example is a sample of input data which has been modified very slightly in a way **that is intended to** cause a machine learning classifier to misclassify it. **In many cases**, these modifications can be so subtle that a human observer does not even notice the modification at all, **yet the classifier still makes a mistake.**

**Tags:** *contrast*

### **Cite previous research results**

**Remarkably**, humans and other animals **seem to solve this problem through a harmonious combination of** reinforcement learning and hierarchical sensory processing systems, **the former evidenced by a wealth of** neural data **revealing notable parallels between the** phasic signals emitted by dopaminergic neurons and temporal difference reinforcement learning algorithms.

**Tags:** *describe, compare, confirm*

**The combination of these methods with the** Long Short-term Memory RNN architecture **has proved particularly fruitful, delivering state-of-the-art results in** cursive handwriting recognition.

**Tags:** *describe, confirm*

**Recent results at the intersection of** Bayesian modelling and deep learning **offer a Bayesian interpretation of common deep learning techniques such as** dropout.

**Tags:** *describe*

**Whereas before 2006 it appears that** deep multilayer neural networks **were not successfully** trained, **since then** several algorithms **have been shown to successfully** train them, **with experimental results showing the superiority of** deeper vs less deep architectures. **All these experimental results were obtained with** new initialization or training mechanisms.

**Tags:** *contrast, confirm, compare*

## Introduce hypotheses

**This grounding of** dropout in approximate Bayesian inference **suggests an extension of the theoretical results, offering insights into the use of** dropout **with RNN models.**

**Tags:** *introduce*

Deep convolutional neural networks (CNNs) **show potential for** general and highly variable tasks across many fine-grained object categories.

**Tags:** *confirm*

## 1.2 Gap

### Cite problems/difficulties

**However RNN performance in** speech recognition **has so far been disappointing, with better results returned by** deep feedforward networks.

**Tags:** *compare*

**A limitation of** LDA **is the inability to model** topic correlation **even though, for example,** a document about genetics is more likely to also be about disease than X-ray astronomy. **This limitation stems from the use of** the Dirichlet distribution to model the variability among the topic proportions.

**Tags:** *contrast, compare*

**Yet a major difficulty with these models is their tendency to overfit,** with dropout shown to fail when applied to recurrent layers.

**Tags:** *contrast*

**However, when** the amount of available data is modest, **there might be** many models that have non-negligible posterior.

**Tags:** *contrast*

**...especially because this new medium is widely exploited as a platform for** disinformation and propaganda.

**Tags:** *describe*

Automated classification of skin lesions using images **is a challenging task owing to the** fine-grained variability in the appearance of skin lesions.

**Tags:** *describe*

**...but existing approaches in NLP still require** task-specific modifications and training from scratch.

**Tags:** *compare*

**Most existing** machine learning classifiers are highly vulnerable to adversarial examples.

**Tags:** *compare*

### **Cite needs/requirements**

**To use** reinforcement learning **successfully in situations approaching** real-world complexity, **however**, agents are confronted with a difficult task: they must derive efficient representations of the environment from high-dimensional sensory inputs, and use these to generalize past experience to new situations.

**Tags:** *introduce, contrast*

**Thus, we want** compute the Bayesian posterior of a feature, i.e., the total posterior probability of all models that contain it.

**Tags:** *introduce*

### **Cite missing issues in previous research**

**While** reinforcement learning agents **have achieved some successes in a variety of domains**, **their applicability has previously been limited to domains in which** useful features can be handcrafted, **or to domains with** fully observed, low-dimensional state spaces.

**Tags:** *compare*

**Up to now**, all previous work **have assumed a threat model in which** the adversary can feed data directly into the machine learning classifier. **This is not always the case for** systems operating in the physical world, **for example those which are using** signals from cameras and other sensors as an input.

**Tags:** *contrast, compare*

### 1.3 Purpose

#### Indicate main purpose

**In this paper**, we propose a new approach for this task.

**Tags:** *define*

#### Introduce purpose with methods

**Here we use recent advances in** training deep neural networks **to develop a novel** artificial agent, **termed a** deep Q-network, **that can** learn successful policies directly from high-dimensional sensory inputs using end-to-end reinforcement learning.

**Tags:** *describe*

**In this paper we develop the** correlated topic model (CTM), **where the** topic proportions exhibit correlation via the logistic normal distribution [J. Roy. Statist. Soc. Ser. B 44 (1982) 139–177].

**Tags:** *describe*

**This paper investigates** deep recurrent neural networks, **which combine the** multiple levels of representation **that have proved so effective in** deep networks with the flexible use of long range context that empowers RNNs.

**Tags:** *describe*

**We apply this new** variational inference based dropout technique in LSTM and GRU models, **assessing it on** language modelling and sentiment analysis tasks.

**Tags:** *describe, introduce*

**This paper introduces a novel approach to influence estimation on social media networks and applies it to the real-world problem of characterizing active influence operations on Twitter during the 2017 French presidential elections.**

**Tags:** *describe, introduce*

**Here we demonstrate** classification of skin lesions using a single CNN, trained end-to-end from images directly, using only pixels and disease labels as inputs.

**Tags:** *describe*

**We propose** Universal Language Model Fine-tuning (ULMFiT), an effective transfer learning **method that can be applied to any task in NLP, and introduce techniques that are key for fine-tuning a language model.**

**Tags:** *introduce, describe*

### **Introduce purpose with results**

**This paper shows that even in such physical world scenarios,** machine learning systems are vulnerable to adversarial examples.

**Tags:** *introduce*

### **Introduce purpose with Gap**

**Our objective here is to understand better why** standard gradient descent from random initialization is doing so poorly with deep neural networks, **to better understand these recent relative successes and help design better algorithms in the future.**

**Tags:** *introduce*

## **1.4 Methods and Materials**

### **Describe methods and materials**

**We tested this agent on the challenging domain of classic Atari 2600 games.**

**Tags:** *describe*

**We apply the CTM to the articles from Science published from 1990–1999, a data set that comprises 57M words.**

**Tags:** *describe*

**We then use this result as the basis for an** algorithm that approximates the Bayesian posterior of a feature. **Our approach uses a** Markov Chain Monte Carlo (MCMC) method, but over orders rather than over network structures.

**Tags:** *describe*

**The new** influence estimation **approach attributes impact by accounting for** narrative propagation over the network. **This grounding of** network causal inference framework **applied to data arising from** graph sampling and filtering.

**Tags:** *introduce, describe*

We train a CNN using a dataset of 129,450 clinical images—two orders of magnitude larger than previous datasets — consisting of 2,032 different diseases. **We test its performance against** 21 board-certified dermatologists on biopsy-proven clinical images with two critical binary classification use cases: keratinocyte carcinomas versus benign seborrheic keratoses; and malignant melanomas versus benign nevi. The first case represents the identification of the most common cancers, the second represents the identification of the deadliest skin cancer.

**Tags:** *describe*

**We demonstrate this by** feeding adversarial images obtained from cell-phone camera to an ImageNet Inception classifier and measuring the classification accuracy of the system.

**Tags:** *describe*

### **Introduces new method contrasting with existing approaches**

**This** causal **framework** infers the difference in outcome as a function of exposure, **in contrast to existing approaches that** attribute impact to activity volume or topological features, **which** do not explicitly measure nor necessarily indicate actual network influence.

**Tags:** *contrast*

Cramér-Rao estimation bounds **are derived for** parameter estimation as a step in the causal analysis, **and used to achieve** geometrical **insight on the** causal inference **problem**.

**Tags:** *describe*

## 1.5 Main Results

### Describe the results

**We demonstrate that the** deep Q-network agent, receiving only the pixels and the game score as inputs, **was able to surpass the performance of all previous algorithms and achieve a level comparable to that of a professional human games tester** across a set of 49 games, using the same algorithm, network architecture and hyperparameters.

**Tags:** *describe, compare*

**When** trained end-to-end with suitable regularisation, **we find that** deep Long Short-term Memory RNNs **achieve a** test set error of 17.7% **on the** TIMIT phoneme recognition **benchmark** (...)

**Tags:** *describe*

**We derive a** fast variational inference algorithm for approximate posterior inference in this model (...)

**Tags:** *introduce*

**The new approach outperforms existing techniques, and to the best of our knowledge improves on the** single model state-of-the-art in language modelling with the Penn Treebank (73.4 test perplexity)

**Tags:** *compare*

**We present empirical results on** synthetic and real-life datasets **that compare our approach to** full model averaging (when possible), to MCMC over network structures, and to a non-Bayesian bootstrap approach.

**Tags:** *compare*

**The ability to** infer high causal influence **is demonstrated on** real-world social media accounts that are later independently confirmed to be either directly affiliated or correlated with foreign influence operations using evidence supplied by the U.S. Congress and journalistic reports.

**Tags:** *describe*

**Our method significantly outperforms the state-of-the-art on** six text classification tasks, reducing the error by 18-24% on the majority of datasets. **Furthermore, with only** 100 labeled examples, **it matches the performance of** training from scratch on 100x more data.

**Tags:** *compare*

## Outline the results

**We first show how to** efficiently compute a sum over the exponential number of networks that are consistent with a fixed order over network variables. **This allows us to** compute, for a given order, both the marginal probability of the data and the posterior of a feature.

**Tags:** *enumerate, describe*

The CNN **achieves performance on** par with all tested experts across both tasks, **demonstrating an** artificial intelligence **capable of** classifying skin cancer **with a level of competence comparable to** dermatologists.

**Tags:** *describe, compare*

## Comments about the results

**...which to our knowledge is the best** recorded score.

**Tags:** *compare*

**...which is complicated by the fact that** the logistic normal is not conjugate to the multinomial.

**Tags:** *describe*

## Describe methods and results simultaneously

**We first observe the** influence of the non-linear activations functions. **We find that** the logistic sigmoid activation **is unsuited for** deep networks with random initialization **because of its** mean value, which can drive especially the top hidden layer into saturation. **Surprisingly, we find that** saturated units can move out of saturation by themselves, **albeit slowly, and explaining the** plateaus sometimes seen when training neural networks. **We find that a new** non-linearity that saturates less **can often be beneficial. Finally, we study how** activations and gradients vary across layers and during training, **with the idea that** training may be more difficult when the singular values of the Jacobian associated with each layer are far from 1. **Based on these considerations, we propose a new** initialization scheme **that brings** substantially faster convergence.

**Tags:** *enumerate, describe*

## 1.6 Conclusion

### Outline conclusions

The CTM gives a better fit of the data than LDA, and **we demonstrate its use as an** exploratory tool of large document collections.

**Tags:** *describe*

**Outfitted with** deep neural networks, mobile devices **can potentially extend the reach of** dermatologists outside of the clinic. **It is projected that** 6.3 billion smartphone subscriptions will exist by the year 2021 (ref. 13) **and can therefore potentially** provide low-cost universal access to vital diagnostic care.

**Tags:** *describe*

**We find that** a large fraction of adversarial examples are classified incorrectly even when perceived through the camera.

**Tags:** *confirm*

### Outline contributions/importance of research

**This work bridges the divide between** high-dimensional sensory inputs and actions, **resulting in the first** artificial agent **that is capable of** learning to excel at a diverse array of challenging tasks.

**Tags:** *confirm*

**This extends our arsenal of** variational **tools in** deep learning.

**Tags:** *describe*