Cat Basis Purrsuit

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Abstract

Meow miao mew meow mew meow mew mew meow miao meow meow mew meow meow miau mew miao meeeow meow, miau meow miao mew meeeeow mew miao miao miao. Meow miao mew meow mew (MMM), meow miao mew meow mew meow, meow meow miao meow state-of-the-art meow meow.

Mew mew meow miao miao nyan nyan meow mew. Meow meow miauw meow miao mew meow, meiau meow meow mew miaou miiiaou. Miao meow meow mew miao meow meow miao miao miau meow miau: meow meow mew mew MMM meow miu meow meow nyan meow mew meow.

1. Introduction

Everyone loves cats.

2. Related work

Fueled by the desire to take advantage of the Internet's cat lust, the last few years have seen a great deal of feline-related work from the machine learning and computer vision communities. These have ranged from attempts to simulate a cat brain (Ananthanarayanan et al., 2009) to using massive amounts of grad students and computational resources to build visual cat detectors (Le et al., 2011; Fleuret & Geman, 2008; Parkhi et al., 2012).

In this paper we hope to take advantage of people's fascination for cats to achieve recognition and adoration for minimum amounts of work.

Proceedings of the 7th ACH SIGBOVIK Special Interest Group on Harry Quechua Bovik. Pittsburgh, PA, USA 2013.

3. Method

One method is to use purrincipal catponent analysis, in which we build a pawsitive definite matrix and extract its eigenvectors. But the problem is that it is not spurrse. We want a spurrse basis [1]. To get the spurrse basis we use the latest in optimization algorithms, Cat Swarm Optimization (CSO) (Chu et al., 2006). A variant of Particle Swarm Optimization (PSO) (Kennedy & Eberhart, 1995), CSO has been used on many applications, including system identification (Panda et al., 2011) and clustering (Santosa & Ningrum, 2009).

CSO is based on the behavior of cats. Through extensive research, it was found that cats spend most of their time sleeping, giving humans dirty looks, and observing the environment. Only when a tasty animal or laser pointer appears does the cat expend energy pursuing a target. CSO refers to these behavioral modes as "seeking mode" (seeking something to attack) and "tracing mode" (actively chasing a target). By randomly sprinkling N cats in the M-dimensional solution space, letting them chase high-dimensional entities, and creating copies of the most fit cats [2], CSO achieves significant gains over alternate optimization approaches (e.g., Mewton's method).

4. Application - Personalized Feline Subspace Identification

To demonstrate the power and potential monetization of our approach, we apply it to the task of Personalized Feline Subspace Identification (PFSI), or the identification of the feline subspace which best represents a person. In addition to being of great theoretical interest, PFSI has obvious monetary potential (due to the cats – duh), meaning it is a problem of interest to

[1] Can haz spurrsity? Only if haz restricted isometry property.

[2] DF: DM, can you please check whether this is approved by the animal research board. I'm pretty sure trans-dimensional projection and copying of mammals is prohibited under our funding contract.

practitioners.

We take a collection of pictures of kitties (denoted $\mathcal{K}$), painstakingly collected by some poor graduate student, and attempt to reconstruct a person's face as a linear sum of the kitties $\mathcal{K}$. Note that we operate directly in the image domain, rather than in the frequency domain with a furrier basis. This is because past experiments have left us with hairballs in our mouth; we hope to find a suitable kernel to sidestep this issue, as was done with the Kardashian space (Fouhey & Maturana, 2012). We apply our Cat Basis Purrsuit approach to discover the spurrse basis that best represents the image. We present visualizations of the first n spurrse basis elements of a variety of leaders and distinguished scientists in Fig. 1. In addition to forming a compact representation, we can also train a discriminative classifier using the coefficients of the catponents (e.g., to classify people into cat-egories, such as "persian" or "tabby"); initial experiments suggest that random furrests work well for this task.

5. Results and future work

We have only "scratched" the surface of the many possibilities for cat-based machine learning and pawttern learning. In a journal version of this work, we hope to horribly mangle cat-based machine learning and bring its head as a present to someone in our household.

One possible further application is to extend this method into the audio domain. This would be a more principled version of works such as the "meow christmas"[3].

Similarly, CSO is limited to continuous domains; we could extend it to develop furry logic systems for control.

Moreover, by feeding the output of our cat basis as input features to another layer of our algorithm, we can build Deep Cat Basis, which is closely related to Hierarchical Feline Stacking; see figure 2.

While CSO is capable of dealing with complex nonlinear problems we would prefer to formulate a convex version of our cost function, in order to leverage the power of our online convex programming algorithm, SWAGGR (Maturana & Fouhey, 2013). See figure 3.

We hope this paper will ignite a revolution in feline-based machine learning and artificial intelligence. In anticipation of the deluge of research in this area we have created a new venue for the presentation of this work, the Conference in Advanced Technology and Neural Information Processing Systems (CATNIPS). This conference will be colocated with the 2013 "Steel City Kitties" cat show in Pittsburgh, Pennsylvania.

[3]http://www.youtube.com/watch?v=vW6ggxViqqo

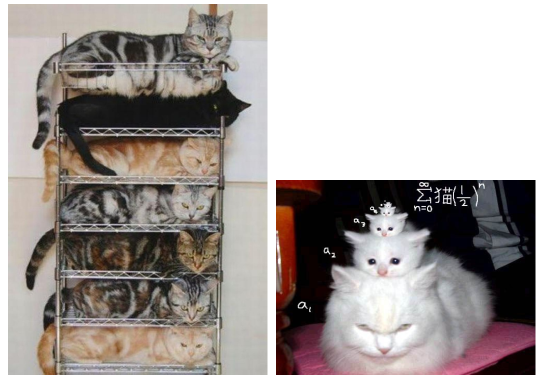

Figure 2. The Deep Cat Basis and Hierarchical Feline Stacking.

Figure 3. A convex formulation.

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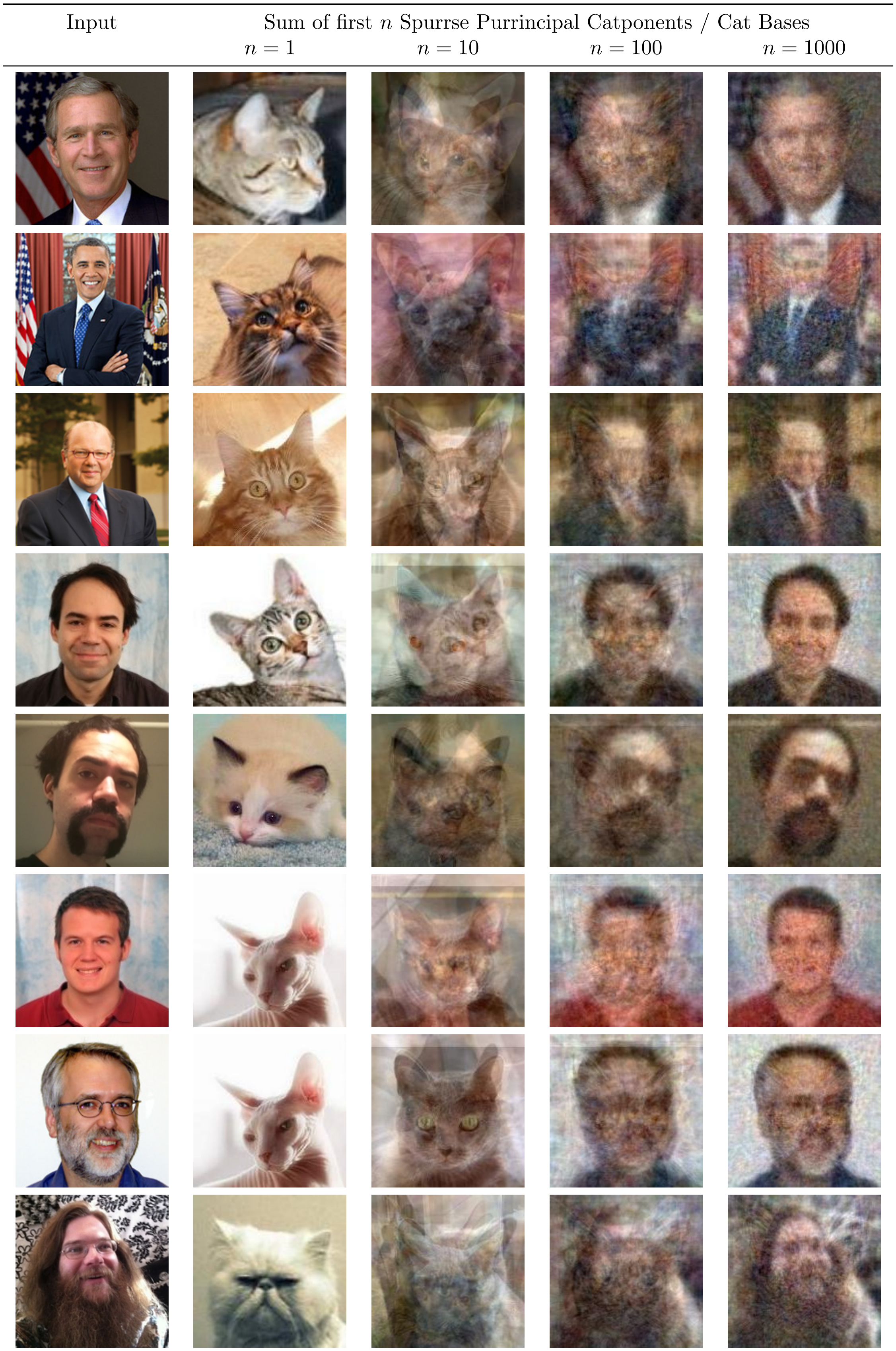

Figure 1. We present the sum of the first n Purrincipal Catponents and use this to do personalized feline subspace identification. Our results are empirically effective, intuitive, and cute (figure best viewed in color).

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