SuperCone: Modeling Heterogeneous Experts with Concept Meta-learning for Unified Predictive Segments System

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ABSTRACT
Understanding users through predicative segments play an essential role for modern enterprises for more efficient and efficient information exchange. For example, by predicting whether a user has particular interest in a particular area of sports or entertainment, we can better serve the user with more relevant and tailored content. However, there exists a large number of long tail prediction tasks that are hard to capture by off the shelf model architectures due to data scarcity and task heterogeneity. In this work, we present SuperCone, our unified predicative segments system that addresses the above challenges. It builds on top of a flat concept representation [1] that summarizes each user’s heterogeneous digital footprints, and uniformly models each of the prediction task using an approach called “super learning”, that is, combining prediction models with diverse architectures or learning method that are not compatible with each other or even completely unknown. Following this, we provide end to end deep learning architecture design that flexibly learns to attend to best suited heterogeneous experts while at the same time learns deep representations of the input concepts that augments the above experts by capturing unique signal. Experiments show that SuperCone can outperform state-of-the-art recommendation and ranking algorithms on a wide range of predicative segment tasks, as well as several public structured data learning benchmarks.

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1 INTRODUCTION
Ever since the introduction of large scale information exchange service such as AOL, Yahoo, Google, and scalable storage and computation infrastructure such as Hadoop, accurately understanding user for customization of information has gradually become one of the most crucial technology that drives the growth and business operation of the service. A tiny variation of the model performance may result in significant downstream impact in user satisfaction and operation revenue [2]. An typical paradigm that is widely adopted in the industry is the predicative segments system. As shown in Figure 1, segments such as user’s interest in a particular category such as entertainment, sports or vehicles can be obtained in order for the users to customize the site and for the online advertisers to effectively budget their campaign. [3] [1] [2].

Current industrial ranking and recommendation approaches [4, 5] is not suitable for unified predicative segments system due to the following reasons:

- **Task Heterogeneity**: Digital footprints such as user’s online activities may be logged and integrated from a wide range of physical machine types and business domain with overwhelmingly large amount of data schema and therefore are hard to be capture by single learning system.
- **Data Scarcity**: The “implicit feedback” [6] nature and missing at random (MAR) effect of available learning signals, the commitment to protect the privacy of consumers and compliance to regulation such as GDPR, and the increasing restrictions from the platform such as Chromageddon [7], Intelligent Tracking Prevention [9] and App Tracking Transparency [3] all contribute to the scarcity of data. Algorithm that relies on rich and complete dataset will suffer from efficiency or effectiveness drop.
- **Long tailness**: The fine granularity of predicative segments that benefit information customization also lead to large number of long tail predicative segments tasks. Many important segments that are critical for the end goal may lack sufficient signal or observations, further aggravating the performance drop of the many existing approaches.

To address the above challenges, we present SuperCone, our unified predicative segments system that builds on distributed concept

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1 https://www.facebook.com/business/ads/ad-targeting
2 https://support.google.com/google-ads/answer/2497941?hl=en
3 https://developer.apple.com/documentation/apptrackingtransparency
representation [10, 11] for constructing reliable representation of signal from heterogeneous signals for each task, and uniformly model each of the prediction tasks using super learning [12], and leverage principled meta learning framework to efficiently learn and combine prediction models with diverse architectures or learning method, while at the same time learns deep representations of the original input signals to augment these experts.

Our contribution can be summarized as follows:

- We study the novel problem of building universal predictive segments for uniformly modeling the large number of fine grained prediction tasks for each predictive segment.
- We present SuperCone as an end to end solution using an architecture that efficiently learns and combines arbitrary heterogeneous prediction models following a principled meta learning framework with provable performance advantage over other possible learners.
- We conduct extensive evaluations SuperCone over a large number of predicative segments task to demonstrate that it substantial performance gain over the state of the art recommendation and ranking approaches, and the previous production system as well as insights and interpret-ability study of its performance.
- We apply SuperCone to structured data learning problem and reports its performance on several public data-sets to further demonstrates the generalization of our approach.

The rest of this paper is organized as follows: In Section 2, we describe related work for building universal predictive segments with super learning. In Section 3, we provide overview of the problem and introduce key terminologies. Next, we talk about our proposed approach in terms of the parameter space and learning procedure. In Section 5, we the key research questions for the evaluation methodology and experiments results for our proposed framework. We finally conclude with our findings in Section 6.

2 RELATED WORK

In this section, we discuss key related work in relations to SuperCone for the four following categories: Industrial Ranking and Recommendation System, Concept Learning, meta learning and super learning.

2.1 Industrial Ranking and Recommendation System

Industrial ranking and recommendation system are key to many aspects of internet business in key areas including advertising [13, 14] and content serving [15, 15–19], with majority of the approaches following point wise paradigm [4, 15, 20] for predicting single numeric score for each given objects, For example, by predicting the likelihood of engagement [4, 5, 21] such as satisfaction and/or final conversion.

These scoring model can be augmented with efficient candidate generation methods from multiple view of implicit feedback [17, 22, 23], solicitation approaches such as exploration and exploitation [24, 25], and deployed along with sophisticated content creation [26–28] and retrieval based recommendation [29, 30] methods to proactively attract users at aggregated level [28, 31].

Our work differs from the above by following novel super learning architecture to incorporate heterogeneous experts and apply it in the predictive segments scenario with data scarcity and long tailness challenge.
2.2 Concept Learning

The research on concept learning [11, 32, 33] focuses on mining concepts from heterogeneous sources such as relational data and semi-structured data lake [34, 35] or from unstructured data [36–38], traditionally through unsupervised clustering and embedding [35, 39, 40] distant supervision [36] or a combination with few-shot learning [417]. Successful concept representation from unstructured in formation can therefore be obtained for downstream analytical tasks [41–44] More recent work focuses specifically on obtaining reliable flat concept representation from heterogeneous information such as user’s implicit feedback [10] for distributed learning systems. Our builds on top of previous work and further learns the interplay across concepts for downstream prediction tasks based on the super learning approach.

2.3 Ensemble Learning

The research on ensemble learning [45] focuses on leveraging multiple machine learning models, commonly referred to as “experts”, and are often bring theoretical and parasitical benefits to the learning process by reducing the variance [46] and are especially known for creating models with strong performance using weaker individual “experts” [47] and being available to build some of the best performing model classes [48]. A particular branch known as “super learning” in statistics [12] focuses on training on machine learning model such as a regression model for combining the predictions of individual “experts” into the final prediction. It is shown in [49, 50] that super learning is the optimal learner in the sense that it will be no worse than the best “experts” irrespective of whether it will converge to true data distribution, and apply it to model classes such as splines, regression models and decision trees. Our method bring a couple of theoretical and practical advancement for the field of super learning including a much more generalized scheme for combining the “experts” with provable optimality guarantee and novel architecture for representation learning.

2.4 Meta Learning

The research of meta learning, also known as “learning to learning”, focuses on learning mechanism that gains experience and improves its performance over multiple learning episodes. [51–53], It has increasing data and compute efficiency and its correspondence with the natural process of animal and human learning [547–56]. One of the most general class of all is the architectural search [57, 58], where multiple instantiation of the model are learned jointly with most performing ones being kept [59, 60] and unfitted ones being discarded [61]. Our work study the meta learning in the context of optimizing the learning of heterogeneous experts in building universal predictive segments, and further investigate learning separate experts to complementing representation power of the rest of experts.

3 PROBLEM OVERVIEW

As illustrated in Figure 2, our unified system of predictive segments will ingest items of interests from a large number of diverse domains such as Hosted Content, Mobile, Advertisement and Finance with a diverse range of knowledge enrichment, resulting in a heterogeneous information network of users and events, and existing segments. As a result, the input to our problem is a data-set containing heterogeneous information with complex and irregular schema and interconnection. To address this, we first leverage distributed AutoML technique from Hadoop-MTA [10] for data integration and transform each the predictive segment task into an equivalent unfolded concept learning task.

Formally, let \( S \) be the set of users (i.e. entity in [10]) that we predict the segment for and \( D \) be the set of possible labels. By following concept unfolding for ingesting heterogeneous information network, where different types of interconnections between entities are serialized as an atomic concept [10]. Consequently, we will have a real-valued concept vector \( c(\zeta) \) for each user \( s \) with index being the list of concept vocabulary \( C \) and value being the intensity of its association to corresponding concepts.

For clarity, we first describe the scenario for learning with homogeneous expert. Specifically, we assume a particular expert \( h_j \), associated with a hypothesis space \( H_j \subseteq \mathbb{R}^C \rightarrow \mathcal{Y} \). We abstract the procedure for training the expert and assume an efficient oracle \( \theta^j(\omega; D) \) for obtaining the trained experts for given dataset \( D \) and meta-parameter \( \omega \in \Omega \) for encoding the dependency on the assumptions for “learning to learn”, such as model hyper-parameters [57, 58, 62].

\[
\min_{\omega \in \Omega} \sum_{s \in D} L_j(h_j(c_s; \theta_j), y(s))
\]

in the hope of minimizing the generalization error. Here \( \theta_j \) is the set of learn-able parameters contained in the parameter space \( \Theta_j \), and \( L_j \) is the loss used for training \( h_j \), such as the loss function used for back-propagation. The task of unfolded concept learning task with homogeneous expert can be stated as follows

**Definition 1 (Unfolded Concept Learning With Homogeneous Expert)**. Assuming the label function of interest \( y : S \rightarrow \mathcal{Y} \) mapping each user to a label in \( \mathcal{Y} \), a probability density of the entity \( q : S \rightarrow [0, 1] \), and a sampled dataset \( D \), the task is to learn a model \( h_j \in H_j \), that minimize the expected risk according to a given criteria

\[
\minimize_{\omega \in \Omega} \mathbb{E}_q[L(h_j(\cdot; \theta_j^s(\omega; D)), y(s))]
\]

where \( \theta_j \in \Theta_j \) denotes the task specific parameter and \( \omega \in \Omega \) denotes meta-parameter. Generalization is then measured by evaluating a number of test points with known labels, \( L \) is the initial value [63] or optimizer for \( \theta_j [53, 64, 65] \).

We start the discussion of unified predictive segments problem by formalizing the meta-learning problem in a more general setting. Consider a distribution over tasks \( p_T : T \rightarrow [0, 1] \), we first assume a source (i.e. meta training) dataset of \( M \) tasks sampled from \( T \), each containing a training set (i.e. support set in meta learning literature [54]) and validation set (query set in meta learning literature [54]) with non-overlapping i.i.d. samples drawn from instances distribution \( q_T \) of task \( T_j \), as \( q_T \text{train} = (q^\text{train}_T, q^\text{valid}_T) \). Likewise, we assume a target dataset (i.e. meta test) \( Q \) of \( Q \) tasks sampled from \( T \), each containing a training set (i.e. support set
in meta learning literature [54] and validation set (query set in meta learning literature [54]) with non-overlapping i.i.d. samples drawn from instances distribution \( q_j \) of task \( T_j \), where \( \mathcal{D}_{\text{target}} \triangleq (\mathcal{D}_{\text{train}}^{(j)}, \mathcal{D}_{\text{test}}^{(j)}) \). The goal is to obtain the "meta knowledge" in the form of \( \omega \) from \( \mathcal{D}_{\text{source}} \) which will then be applied to improve downstream task specific performance in \( \mathcal{D}_{\text{target}} \), by adapting and improving based on the individual training set of in the target set in the hope of generalization to the test set.

For the task of learning with heterogeneous experts, however, we are not constrained to the case where source and target set are separate. Specifically, we only require one dataset \( \mathcal{D} \) to serve as the source dataset, for meta-training, and one target dataset, for meta-test. We assume each of task \( j, j = 1 \ldots J \), where the only difference between tasks is the particular expert \( h_j \), each associated with a hypothesis space \( \mathcal{H}_j \subseteq \mathbb{R}^C \rightarrow \mathcal{Y} \), a set of learn-able parameter \( \theta_j \in \mathcal{H}_j \), and a training oracle \( \theta_j^* (\omega; \mathcal{D}) \) satisfying ??. The end goal of meta training, then, is to obtain optimal generalization error on the single test target set.

Formally, we assume all the available instances will be used for both the source and target set. Given a sample of data \( \mathcal{D} \triangleq \{\mathcal{D}_{\text{train}}, \mathcal{D}_{\text{test}}\} \), drawn i.i.d from the distribution \( q(s) \). We will use some or all of the instances from \( \mathcal{D}_{\text{train}} \) for training the individual experts \( h_j (:; \theta_j, \omega) \), i.e. \( \mathcal{D}_{\text{source}}^{(j)} \subseteq \mathcal{D}_{\text{train}} \), \( \mathcal{D}_{\text{source}} \subseteq \mathcal{D}_{\text{train}} \). \( \mathcal{D}_{\text{source}}^{(j)} \cap \mathcal{D}_{\text{source}} = \emptyset \). Likewise, the dataset used for meta-test consume some or all of the training instances, i.e., \( \mathcal{D}_{\text{train}}^{(j)} \subseteq \mathcal{D}_{\text{train}}, j = 1 \ldots J \). The final goal is to learn a joint model based on the adapted experts on the target training set, \( \theta_j^* (\omega; \mathcal{D}_{\text{target}}^{(j)}) \) for \( j = 1 \ldots J \), denoted as \( h(:, \theta_j^* (\omega; \mathcal{D}_{\text{train}}^{(j)}))) \), that achieves the best generalization error. We now have The unfolded concept learning with heterogeneous experts can then be defined as joint learning upon \( f \) inner training tasks as follows.

**Definition 2** (Unfolded Concept Learning With Heterogeneous Experts). Assuming the label function of interest \( y : \mathcal{S} \rightarrow \mathcal{Y} \), a sampled dataset \( \mathcal{D} \), a set of heterogeneous experts \( h_j \) with inner training oracle \( \theta_j^* (\omega; \mathcal{D}) \) for \( j = 1 \ldots J \), the task is to learn a combined model \( h \) that minimize a given loss criteria \( L : \mathcal{Y} \times \mathcal{Y} \rightarrow \mathbb{R} \)

\[
\begin{align*}
\text{minimize } & \sum_{s \in \mathcal{D}_{\text{test}}} L((h(c_s; \omega^*), (h_j (:; \theta_j^* (\omega^*; \mathcal{D}_{\text{train}}^{(j)}))))), y(s)) \\
\text{s.t. } & \omega^* = \arg \min_{\omega} L_{\text{meta}} ((\theta_j^* (\omega, .))_{j = 1 \ldots J}, \omega, \mathcal{D}_{\text{train}}) \\
\end{align*}
\]

where \( L_{\text{meta}} \) is a meta loss to be specified by the meta-training procedure, such as the cross entropy error of temporal difference error [63].

The unfolded concept learning with heterogeneous experts abstraction extends unfolded concept learning for efficient and scalable distributed AutoML and retains the representation power. Using its relation to unfolded concept learning problem [10] we have the following results.

**Theorem 1.** The above Unfolded Concept Learning With Heterogeneous Experts problem is no less difficult than the Learning In Heterogeneous Data Problem (Definition 1 in [10], Learning In Relational Database (Definition 2 in [10]), Heterogeneous Graph Learning (Definition 3 in [10]), and First order Logic Graph Learning (Definition 4 in [10]). In fact, there exists efficient linear time reduction from Learning In Heterogeneous Data Problem, Learning In Relational Database, Heterogeneous Graph Learning, and First order Logic Graph Learning to Unfolded Concept Learning With Heterogeneous Experts problem.
4 CHOICE OF $\Omega$

We divide our discussion of meta learning algorithm into two parts, the representation of the meta model and the optimization procedure. In this section, we focus on the first part of the meta parameter space $\Omega$ that will be agnostic to the choice of $\Theta_j$ of individual experts $H_j$.

The solution space induced by meta parameter $\omega$ brings inductive bias to the downstream tasks and affect the efficiency of learning procedure of each task. Several key challenges exist for deploying into critical predictive segments systems

- **Heterogeneous Task Agnosticy** The choice of $\Omega$ should allow flexibly model a large range of tasks of heterogeneous nature and best utilize the power of experts from $\mathcal{H} = \{H_j|j = 1\ldots J\}$ depends on the task to be applied, without task-specific engineering.

- **Representation Power** The choice of $\Omega$ should contain enough representation capacity to allow learning deep representation of data instead of limiting it to specific function class or classification and regression models.

- **First order influence** The influence of meta parameter $\omega$ should allow for efficient optimization for performance critical application without resorting to higher order gradient estimate [63]

Previous approaches mostly fall into the following categories: traditional super learning and ensemble learning approaches [50] are heuristic in nature and fail the second criteria; traditional deep learning approaches [4] fail to incorporate the power of experts and fails the first; meta-learning approaches relies on higher order and bi-level optimization [63] [62] and are disqualified by the third criteria.

To address this, we present our SuperAug architecture that construct a large portfolio of augmented experts and learns deep representation for both direct prediction directly from unfolded concepts and indirect combination of heterogeneous experts, while at the same time respecting their simplicity.

**Experts Expansion** In the first stage of Experts Expansion, we collect possible combinations of experts and construct an augmented set of experts space $\mathcal{H}_{Aug}$ by "cross-breeding" the experts. Specifically, the space of experts $\mathcal{H}_{Aug}$ is constructed such that:

1. any expert model with hypothesis $H$ belonging to $\mathcal{H}$ will also belong to $\mathcal{H}_{Aug}$
2. any arithmetic combination between arbitrary number of experts in $\mathcal{H}_{Aug}$ will also belong to $\mathcal{H}_{Aug}$
3. any recursively application of expert with hypothesis $H$ belonging to $\mathcal{H}_{Aug}$ over an arbitrary number of outputs from $\mathcal{H}_{Aug}$ will also belong to $\mathcal{H}_{Aug}$

The Expert Expansion is implemented in a heterogeneous expert network in SuperAug following a sluice network architecture [66] along with layer by layer skip connections. As shown in Figure 3, the output at each level of densely connected experts $\sigma(\cdot)$ will be fed to both the immediately next level as input as well as to all future levels, and the subsequent connected henceforth.

**Alternative Experts** In order to augment the model capacity and obtain deep representation of the data, we construct an alternative expert with hypothesis $H_{Alt}$ with a neural network architecture
that allow flexible combination of internal components while respect the simplicity of network with lower weights. To that end, we follow a neural mixture of experts scheme that captures modularized information across components [67] with an the MIMO architecture[68]. Specifically, we divide the neural net into the end output module Tower that produce the output for the particular task $E$ inner expert neural networks InnerExpert$_t$, $1 \leq t \leq E$, the gating network Gate$_t$ that project the input into $\mathbb{R}^E$ from concept vector $\vec{c}$. The prediction of the final alternative expert that map concept vector $\vec{c}$ into label space $\mathcal{Y}$, $h_{alt}(\vec{c})$, can be expressed as follows

$$h_{alt}(\vec{c}) = \text{Tower}(\vec{c})$$  \hspace{1cm} (4)

$$v_s = \sum_{t} \text{softmax}(\text{Gate}(\vec{c}))_t \cdot \text{InnerExpert}_t(\vec{c})$$  \hspace{1cm} (5)

where the intermediate representation $v_s$ is a weighted sum by a shallow network Gate$_t(\vec{c}^\text{meta})$ after normalizing to unit simplex via softmax() over inner experts. Each InnerExpert$_t$, in turn, is an ensemble mapping $\vec{c}$ to fixed-length vector. Formally,

$$\text{InnerExpert}_t(\vec{c}) = \sum_{k \in \mathcal{C}} \text{Depth}_t(\vec{c})$$  \hspace{1cm} (6)

$$\text{Depth}_t(\vec{c}) = \text{Proj}_{t,i} \left( \text{Proj}_{t,j-1} \left( \ldots (\text{Embed}(\vec{c})) \ldots \right) \right)$$  \hspace{1cm} (7)

where Depth$_{t,i}$ denotes an intermediate output for the inner expert $t$ at depth $i$, consisting of projection in the form of Proj$_{t,i}$ which is implemented as a linear layer followed by a non-linear activation. As illustrated in the alternative expert component in Figure 3, an ensemble of neural experts will first be combined to form a deep representation from the concept vector, and further combined with the rest of heterogeneous experts.

**Combination Network** One distinctive advantage of SuperAug over traditional ensemble approaches is the ability to adaptively weight in the different predictions across experts based on the instance. Specifically, assuming the experts from $\mathcal{H}_{\text{Aug}}$ are arranged as an array of mappings $\{h_1, h_2, \ldots, h_{\text{Aug}}\}$, the combination network component Comb, will map the concept vector $\vec{c}$ into an $|\mathcal{H}_{\text{Aug}}| + 1$ dimension vector. We follow the DARTS meta-learning [59] architecture and produce final model prediction, $h(\vec{c})$, as another layer of weighted sums over all possible experts

$$h(\vec{c}) = \sum_{t \in \{1,2,\ldots,T\} \cup \{\text{Aug}\}} \text{softmax}(\text{Comb}(\vec{c}))_t \cdot h_t(\vec{c})$$  \hspace{1cm} (8)

**5 META OPTIMIZATION**

In this section we describe the approach for optimizing the meta-parameters $\omega$, agnostic to the heterogeneous experts in $\mathcal{H}$. Naive approach that directly treat the original input dataset $\mathcal{D}$ to compute the meta loss $L^\text{meta}$ or using it as the support set $\{D^{\text{train}}(j)\}$ might lead to “meta-overfit” where the combination network and the added experts in $\mathcal{H}_{\text{Aug}}$ falsely rely on overfitted experts. In contrast, we propose a principled framework to construct meta-training set that eliminates the phenomenon and achieves generalization with provable guarantee. The high level intuition is to extract non-overlapping subset of the data as the support and query set as the source data meta-training to minimize the discrepancy between meta-training and deployment. Our optimization method makes no assumption about the heterogeneous experts, including the existence of gradients in its learning process.

The optimization is shown in Figure 4, where each level of heterogeneous experts is trained recursively on previous levels with its own meta-training set based on the cross-validation split, with the final level corresponding to the SuperAug architecture. Specifically, we can index heterogeneous experts by the depth it depends on other experts, with $h^{(j)}_t$ denoting the $j$th expert at $k$th layer, $k = 1, 2, \ldots, K$. At each depth, we have a cross validation scheme, $V^{(k)}$ mapping instance $s$ from $\mathcal{D}^{\text{train}}$ to a fold among $1, 2, \ldots, V$, the learning proceed by creating higher-order meta training dataset at each $k$th layer, $\mathcal{D}^{\text{train}}(k)$ as

$$\mathcal{D}^{\text{train}}(k) \triangleq \{(x^{(k)}_s, y^{(k)}_s) | x_s \in \mathcal{D}^{\text{train}}(k) \}$$  \hspace{1cm} (9)

with $(\mathcal{D}^{\text{train}}(k))^{-s}$ denoting the subset of $(\mathcal{D}^{\text{train}}(k))$ not in the same fold as instance $i$, formally

$$\mathcal{D}^{\text{train}}(k)^{-s} \triangleq \{V^{(k)}(s) \neq V^{(k)}(s') | x_{s'} \in \mathcal{D}^{\text{train}}(k) \}$$  \hspace{1cm} (10)

And the meta-parameter $\omega$ is trained using the last layer of the constructed meta-training dataset $\mathcal{D}^{\text{source}} \triangleq \mathcal{D}^{\text{train}}(K)$, with respect to the meta loss defined as follows

$$L_{\text{meta}}(\{D^{\text{train}}(j)\}, \omega, \mathcal{D}^{\text{source}}) \triangleq \sum_{x_{s,|\mathcal{C}|}} L(h^{\text{train}}(x_s), y(s))$$  \hspace{1cm} (12)

with the meta-training time model $h^{\text{train}}(x_s)$ defined by replacing the output of all heterogeneous experts directly by taking all but the first $|\mathcal{C}|$ elements from the input, $x_{s,|\mathcal{C}|}$ and feeding the alternative expert and the combination network with the original feature, $x_{s,|\mathcal{C}|}$. Formally,

$$h^{\text{train}}(x_s) \triangleq \sum_{t \in \{1,2,\ldots,T\} \cup \{\text{Aug}\}} v^{(j)}_t \cdot \text{softmax}(\text{Comb}(x_{s,|\mathcal{C}|}))(t) \cdot h_t(\vec{c})$$  \hspace{1cm} (12)

The learning of the network parameter thus become and end-to-end optimization problem which can be solved using efficient gradient based methods [59].

Finally, at meta-test time, the source set for each of the heterogeneous experts $h^{(j)}$, $\mathcal{D}^{\text{target}}(k,j)$ is defined as the $k$th high order meta training dataset, i.e. $\mathcal{D}^{\text{target}}(k,j) \triangleq \mathcal{D}^{\text{train}}(k)$. We also have the following results regarding the model’s asymptotic and finite sample generalization error over arbitrary heterogeneous expert or the meta learning architecture.

**Theorem 2.** Assume $\mathcal{Y}$ with bounded cardinality, for any predictive model $y'$, there exists an parameter space of SuperAug $\Omega$ with the same of less generalization error on instance distribution $q(s)$ for every instantiation of the data $\mathcal{D}$ in an asymptotic sense. Moreover, for float-point based implementation of meta-parameter $\omega$, and $K = 1$, then its generalization error will converge to $0$ or to the best predictive model under a $O\left(\frac{\log n}{n}\right)$ rate.
Proof We start with the case of asymptotic generalization error. Consider an arbitrary predictive model \( h_1(\cdot) \) with a learning oracle \( \theta^*_j(D) \), we construct the following \( \text{SuperAug} \) architecture with a series of heterogeneous experts including \( h_1(\cdot) \). Without loss of generality, we assume it is the first expert with index 1, since the \( \text{SuperAug} \) architecture will further optimize the training time error compared to its input, with probability at least \( 1 - \delta \) we have

\[
\int_{x \in \mathcal{S}} L((h(\tilde{x}^*_i; \omega^*; \{h_j(\cdot; \theta^*_j(\omega^*; D^{\text{train}}(j))\}) \cup y(s))q(s) + \\
\sum_{s \in \mathcal{S}} L((h(\tilde{x}^*_i; \omega^*; \{h_j(\cdot; \theta^*_j(\omega^*; D^{\text{train}}(j))\}) \cup y(s))q(s) + \\
O\left(\sqrt{\frac{C_1 \log |D^{\text{train}}| + C_2 + \log \frac{1}{\delta}}{|D^{\text{train}}|}\right)
\leq \int_{x \in \mathcal{S}} L(h_1(\cdot; \theta^*_1(D^{\text{train}})), y(s))q(s) + \\
O\left(\sqrt{\frac{C_1 \log |D^{\text{train}}| + C_2 + \log \frac{1}{\delta}}{|D^{\text{train}}|}\right)
\]

(13)

where the first and second inequality is established with [69] and \( C_1, C_2 \) are fixed constant. For the second part of the theorem, again consider an arbitrary predictive model \( h_1(\cdot) \), we construct 1 level \( \text{SuperAug} \) architecture with a series of heterogeneous experts including \( h_1(\cdot) \) as the first expert with index 1, along with a series of experts that output the original feature \( \tilde{x}_i \) into the expert combination \( \omega \). If we denote \( h^*(\cdot) \) as the expected risk minimizer and \( d(h, h^*) \leq E_{x \sim q(s)}[L(h(\tilde{x}_i), y(s)) - L(h^*(\tilde{x}_i), y(s))] \) be the expected performance of a model \( h \), by leveraging the results in Equation 2 in [49], from which the convergence results will follow from the fact that for every \( \delta > 0 \) there exists a constant \( C \) that

\[
\frac{1}{V} \sum_{v=1}^{V} Ed(h(\tilde{x}_i; \omega^*; \{h_j(\cdot; \theta^*_j(\omega^*; D^{\text{}}(j)), V^{(0)}(s) = v))\}, h^*)
\leq (1 + \delta)E \min_{v \in \mathcal{V}} \frac{1}{V} \sum_{v=1}^{V} d(h(\tilde{x}_i; \omega^*; \{h_j(\cdot; \theta^*_j(\omega^*; D^{\text{train}}), V^{(0)}(s) = v))
\]

(14)

6 EXPERIMENT

In this section, we present a series of experiments centered around the following research questions:

- **RQ1** How do alternative methods compare to SuperCone according to core performance metrics used for prediction?
- **RQ2** How do the settings and individual components of SuperCone affect its quality?
- **RQ3** How does the approach of SuperCone compares with other methods when applied to public structured data learning tasks?
- **RQ4** Is the approach of SuperCone reliable when applied to different tasks of different types and domains and interpretable to human inspection?
- **RQ5** How does SuperCone perform under resource constrained scenario and balance between the performance and computation cost?
- **RQ6** How does SuperCone compared against alternatives in production environment for key end goals?

**Data-set** We used both proprietary and public datasets. For the former, we collected and compiled a total of 39 different predictive segment tasks involving discretized range prediction, multi-class classification prediction as well as binary classification prediction from production. It is constructed by associating users with interest taxonomy including YCT, OIC [70], as well as open-domain knowledge base including Wikipedia and Price-Grabber. The dataset contains 100K dimensional unfolded vector per instance, with a total of 100K instances. Each of the 39 dataset is split into 3 folds, with 2/3 of them belonging to the support set and remainder belonging to the hold-out query/test set.

We also compare our approaches over several public benchmark dataset. Specifically, we use the made1on[71] and a9a[72]. made1on contains 2,000 training samples, 600 test samples with 500 features per sample. a9a contains 32,561 training samples, 16,281 test samples with 123 features per sample, respectively.

**Methods Comparison** We implement SuperCone in two variants. The first variant is a homogeneous neural network version that predicts the outcome with purely the neural alternative expert \( H_{Alt} \) and the expert combination architecture following a multi-gated neural mixture of expert (MMOE) [4] architecture, where each one is by itself constructed recursively with an MMOE, with the inner MMOE for \( H_{Alt} \) having 3 experts 3 layer of densely connected residual connection as shown in Equation 7 with a width of 32, and gate network having 2 layer of densely connected residual connection shown in Equation 7 with width 32, and the inner MMOE for the combination network having 3 layer of densely connected residual connection as shown in Equation 7 with a width of 32. We denote this the Multi-MMOE. We then use the exact same network architecture and combine it with heterogeneous expert set with \( |H_{Src}| = 70 \) and \( K = 2 \) for public benchmark and the production supported \( |H_{Src}| = 31 \) and \( K = 1 \) experts for the proprietary datasets, including 11 hyperparameter-tuned gradient boosting models under various implementation trained on GPU accelerators.

The learning rate is tuned using an exponent search and set as 1e-4 with epoch of 30. The setting is applied to all datasets. In addition, we implement the following baseline approaches

- **PLE** implements the Progressive Layered Extraction method [5] using shared expert count as 1 and specific expert as 2, with expert layer width as 256, 256, gate layer width as 16, 16, and tower layer depth as 32, 32.
- **WDL** implements wide and deep learning [73] with the deep network layer width tuned as 8 for made1on and 256, 128, 64 tuned for the rest datasets.
- **ESSM** implements Entire Space Multi-Task Model [21] with CTR component and CVR component each with layer width as 512, 512.
- **DCN** implements Deep & Cross Network [74] with layer width as 384, 128, 64, cross count as 2 and cross dimension as 100.
Table 1: Performance evaluation on the public benchmark datasets of *a9a* and *madelon* over the metric: AUC, Accuracy, F1 score, Kappa Cohen Score (Kappa), Log loss against the ground truth. Both the absolute value and relative value compared to WDL baseline are reported.

|          | Accuracy | AUC   | F1    | Log loss | Overall |
|----------|----------|-------|-------|----------|---------|
| WDL      | 0.8217   | 0.8687| 0.5122| 6.1224   | +59.80% |
| PLE      | 0.8495   | 0.8913| 0.6165| 5.6094   | +70.92% |
| MMOE     | 0.8411   | 0.8938| 0.5181| 5.4797   | +70.92% |
| ESSM     | 0.8148   | 0.8774| 0.4289| 5.3961   | +63.53% |
| DCN      | 0.7965   | 0.8433| 0.4201| 5.2701   | +62.61% |
| DCMix    | 0.8043   | 0.8559| 0.4579| 5.3909   | +63.53% |
| DCN      | 0.8071   | 0.8646| 0.4579| 5.3909   | +63.53% |
| SuperCone| 0.8491   | 0.9050| 0.4579| 5.3909   | +63.53% |

**Figure 5:** Performance comparisons of weighted one-versus-result ROC-AUC, weighted F-1 Score, Log loss across the 39 different types of predictive segment tasks.

**Figure 6:** Model cost measured in microseconds over the 39 production predictive segment tasks.
Figure 7: Distribution of change in model performance and model cost across \textit{SuperCone} variants.

Figure 8: Experts attention learned by \textit{SuperCone} averages across datasets

- DCNMix implements Cost-Effective Mixture of Low-Rank DCN [75] with per layer experts count as 4 and width as 256, 128, 64, cross count as 2 and cross dimension as 100 with a rank of 32.

All online adaptation and single task learning was performed with 30 epochs of Adam optimization with a tuned learning rate between 1e-6 and 1e-5 depends on the dataset. The rest settings default to the implementation reported in the original paper.

\textbf{Core Performance Evaluation [RQ1, RQ4]} First and foremost, we compare the performance of various candidate approaches over the 39 production predictive segment tasks, and score their performance using the weighted one-versus-all ROC-AUC (Weighted OVR AUC) that applies to range-prediction, multi-class prediction and binary prediction, as well as the weighted F1 score and cross-entropy log loss that also applies to the different types of prediction tasks simultaneously. As shown in Figure 5, \textit{SuperCone} that is implemented agnostic to tasks does not suffer from overfitting or meta-overfitting, and is able to consistently outperform benchmarks and achieves close to 100 \% F1-score and ROC-AUC without tuning. With other strong baselines including Multi MMOE, PLE and ESSM.

\textbf{Public Benchmark Evaluation [RQ3,RQ4]} We further evaluate the applicability of \textit{SuperCone} on public structured dataset against the best performing version of baselines, where the Multi MMOE methods degrades to MMOE architecture [25]. Table 1 reports the absolute value of various performance metrics including Accuracy, ROC-AUC (AUC), Cohen-Kappa Score (Kappa), F1 Score (F1) and Log loss, as well as its relevant change compared to baseline WDL of and the aggregated the overall change across metrics. Again, \textit{SuperCone} without task specific tuning is able to achieve consistent performance, improving on competitive baseline by a significant margin.

\textbf{Computation Cost [RQ5]} We then study the computation cost of various approaches that are of critical importance for cost and latency sensitive production system. Specifically, we measure the computational cost in a per distributed-executor node setting, where sharded dataset are sent to local node and processed sequentially. Figure 6 shows the number of microsecond to process a single data instance, where \textit{SuperCone} requires similar cost because heterogeneous expert outputs only amounts to small portion of the feature sets, and thus achieving a better tradeoff point between performance and cost.

\textbf{Ablation Analysis [RQ2]} We investigate the impact of meta training over heterogeneous experts (see Algorithm 1) by comparing the distribution of performance gain and cost change in terms of Weighted OVR ROC-AUC over from \textit{SuperCone} and its ablation version without heterogeneous experts, i.e. the Multi MMOE approach. The left figure of Figure 7 shows the distribution of relative gain in performance while the right figure of Figure 7 shows the distribution of relative cost, aggregated over the 39 production predictive segment tasks. We can observe that \textit{SuperCone} achieve a significant improvement over the already competitive ablation version with cost distributed closely around zero in a highly symmetric fashion.

\textbf{Interpret-ability Study [RQ2,RQ3]} We next investigate the interpret-ability of \textit{SuperCone} by visualizing the meta-learned expert attention average across instances and datasets for the domain of proprietary predictive segments tasks, \texttt{madelon}, and \texttt{a9a}. Specifically, for each dataset, we extract the instantiated combination network output softmax(Comb(\(\bar{z}^{(u)}\))) as shown in Equation 8, for the |\(\mathcal{H}_{\text{Aug}}\)| + 1 experts, with neural alternative methods followed by the heterogeneous experts. As shown in Figure 8, expert attention displays an even distribution across the multiple experts, with the proprietary domain more biased towards models with GPU accelerator and scale to dataset with much larger instances count and more features.

\textbf{Online evaluation [RQ6,RQ4]} The \textit{SuperCone} is rolled out to production targeting use cases in internal Hadoop based deployment system and evaluation in key range prediction tasks Table 2 shows the performance comparison between \textit{SuperCone} and previous production system, which shows that the meta-training paradigm generalizes well to the new incoming data and compares favorably in the practical setting.

\begin{table}[h]
\centering
\begin{tabular}{|c|c|c|c|c|}
\hline
Previous Production & & & & \\
\hline
\textit{SuperCone} & 0.20 & 0.23 & 0.28 & 0.21 & 0.08 \\
\textit{SuperCone} & 0.42 & 0.42 & 0.42 & 0.41 & 0.27 \\
\hline
Lift & +112.54\% & +78.47\% & +47.39\% & +89.85\% & +249.61\% \\
\hline
\end{tabular}
\caption{Comparison of \textit{SuperCone} with the previous production system on range prediction use cases}
\end{table}

7 CONCLUSION

In this work, we present \textit{SuperCone} as our solution for predicative segments system that is able to handle task heterogeneity, data scarcity and long tailness, by integrating heterogeneous experts and combining them in the end to end fashion, following a principled meta-learning approach. Extensive evaluation on large number of predicative segments tasks and public benchmarks datasets demonstrate the reliability and superior performance of \textit{SuperCone} over
state of the art recommendation and ranking approaches in key production use cases.

One particular interesting directions for future research is to extend the SuperCon paradigm for wider range modality and domain and more applications tasks for social good, another is to build more universal representation and better integration with common knowledge base towards commonsense AI.

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A DETAILS ON META OPTIMIZATION

We present the SuperAug Algorithm in Algorithm 1 that operates on the unfolded concepts. It constructs the meta-training set for experts from level 1 to level K in a bottom-up progressive fashion following the cross validation scheme (line 2-7), by using the Kth layer of the meta-data-set for end to end training of meta parameters (line 8), the meta-testing time model can be obtained by adapting on the support set which covers every individual user in the training data as the (line 9-13) and combine them according to original Model architecture (line 14).

The above algorithm for \( O(K \cdot J \cdot \frac{n_{\text{experts}}}{n_{\text{meta}}} + 1 \) compared to vanilla differentiable architecture training with \( \frac{n_{\text{experts}}}{n_{\text{meta}}} \) being the ratio of average training cost between one single heterogeneous experts and the differentiable architecture.

B DETAILS ON THE SUPERCONE IMPLEMENTATION

SuperCone is implemented using the exact same hyper-parameter and optimization setting as the Multi MMOE model, together with recursively constructed heterogeneous experts (line 2-7 in Algorithm 1). For public benchmark, we use a expert set with \( |\mathcal{H}_{\text{aug}}| = 70 \) and \( K = 2 \), including 14 gradient boosting tree variants, 1 separately trained relu neural network variant, 8 bagging tree variants, 7 generalized linear model variants, 1 Bayesian graphical model variant, 1 nearest neighbor variant, 1 Adaboost variant and 2 SVM variant with model implementation choice tuned set cross validation. The heteroge-neous experts are trained on a subset of the corresponding support set which covers every individual user in the training data (see Figure 4) within a time budget of 30 minutes. These same setting is applied to all datasets in the corresponding domain.

C DETAILS ON CORE PERFORMANCE EVALUATION

We compare the performance various candidate approaches over the 39 production predictive segment tasks Figure 9 and Figure 10 shows the Kappa Cohen score and accuracy for all tasks, further demonstrating that SuperCone is able to achieve consistently high performance using simple parameter configurations.

D DETAILS ON THE PUBLIC BENCHMARK EVALUATION

We show the receiver operating curve for a9a dataset in Figure 11 and the receiver operating curve for madelon dataset in Figure 12, further confirming the superior performance of SuperCone of dataset with different difficulties.

E DETAILS ON THE ABLATION STUDY

Figure 13 shows the difference between SuperCone and its ablation version without heterogeneous experts in the commonly compared cross entropy log loss. Specifically, the distribution of relative change in the log loss across all the predictive segments tasks are drawn, from which we can observe a consistent trend of loss reduction.

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Algorithm 1 SuperAug Algorithm

Require: label function of interest \( y : S \rightarrow Y \), a sampled dataset \( D \pm \{D_{\text{train}}, D_{\text{test}}\} \) with each instance associated with concept vocabulary \( C \), heterogeneous experts \( h_j \) with inner training oracle \( \delta_j^0(\omega, D) \) for \( j = 1 \ldots J \)

Require: \( K \): maximum depth for constructing experts, \( V \): number of possible values for cross validation scheme

1: \( D_{\text{train}}(0) \leftarrow D_{\text{train}} \)
2: for all \( k \in \{1 \ldots K\} \) do
3: for all \( s \in D_{\text{train}} \) do
4: \( V^{(k)}(s) \leftarrow \text{random draw from } \{1 \ldots V\} \)
5: end for
6: construct \( D_{\text{train}}(k) \) according to Equation 9, Equation 10 and Equation 11
7: end for
8: obtain meta-trained \( \omega^* \) according to Equation 12
9: for all \( k \in \{0 \ldots K\} \) do
10: for all \( j \in \{1 \ldots J\} \) do
11: adapt experts \( h_j^{(k)} \) from support \( D_{\text{target}}^{(k,j)} \) according to ??
12: end for
13: end for
14: obtain final model based on the optimized meta parameter and adapted experts according to
Figure 9: Core performance comparison as measured by Kappa Cohen score over all predictive segment tasks

Figure 10: Core performance comparison as measured by accuracy over all predictive segment tasks

Figure 11: Receiver Operating Curve of SuperCone on public benchmark data a9a for both classes

Figure 12: Receiver Operating Curve of SuperCone on public benchmark data m5a7 for both classes

Figure 13: Distribution of change in cross entropy log loss between SuperCone and its ablated version