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Besting the Quiz Master: Crowdsourcing Incremental Classification Games

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Abstract

Cost-sensitive classification, where the *features* used in machine learning tasks have a cost, has been explored as a means of balancing knowledge against the expense of incrementally obtaining new features. We introduce a setting where humans engage in classification with incrementally revealed features: the collegiate trivia circuit. By providing the community with a web-based system to practice, we collected tens of thousands of implicit word-by-word ratings of how useful features are for eliciting correct answers. Observing humans' classification process, we improve the performance of a state-of-the art classifier. We also use the dataset to evaluate a system to compete in the incremental classification task through a reduction of reinforcement learning to classification. Our system learns **when** to answer a question, performing better than baselines and most human players.

1 Introduction

A typical machine learning task takes as input a set of features and learns a mapping from features to a label. In such a setting, the objective is to minimize the error of the mapping from features to labels. We call this traditional setting, where all of the features are consumed, *rapacious* machine learning.[1]

This is not how humans approach the same task. They do not exhaustively consider every feature. After a certain point, a human has made a decision and no longer needs additional features. Even indefatigable computers cannot always exhaustively consider every feature. This is because the result is time-sensitive, such as in interactive systems, or because processing time is limited by the sheer quantity of data, as in sifting e-mail for spam (Pujara et al., 2011). In such settings, often the best solution is incremental: allow a decision to be made without seeing all of an instance's features. We discuss the incremental classification framework in Section 2.

Our understanding of how humans conduct incremental classification is limited. This is because complicating an already difficult annotation task is often an unwise tradeoff. Instead, we adapt a real world setting where humans are already engaging (eagerly) in incremental classification—trivia games—and develop a cheap, easy method for capturing human incremental classification judgments.

After qualitatively examining how humans conduct incremental classification (Section 3), we show that knowledge of a human's incremental classification process improves state-of-the-art *rapacious* classification (Section 4). Having established that these data contain an interesting signal, we build Bayesian models that, when embedded in a Markov decision process, can engage in effective incremental classification (Section 5), and develop new hierarchical models combining local and thematic content to better capture the underlying content (Section 7). Finally, we conclude in Section 8 and discuss extensions to other problem areas.

2 Incremental Classification

In this section, we discuss previous approaches that explore how much *effort* or resources a classifier chooses to consume before it makes a decision, a problem not as thoroughly examined as the question of whether the decision is right or not.[2] Incremental classification is *not* equivalent to *missing* fea-

[1]Earlier drafts called this "batch" machine learning, which confused the distinction between batch and online learning. We adopt "rapacious" to make this distinction clearer.

[2]When have an *externally* interrupted feature stream, the setting is called "any time" (Boddy and Dean, 1989; Horsch and Poole, 1998). Like "budgeted" algorithms (Wang et al., 2010), these are distinct but related problems.

tures, which have been studied at training time (Cesa-Bianchi et al., 2011), test time (Saar-Tsechansky and Provost, 2007), and in an online setting (Rostamizadeh et al., 2011). In contrast, incremental classification allows the learner to decide whether to acquire additional features.

A common paradigm for incremental classification is to view the problem as a Markov decision process (MDP) (Zubek and Dietterich, 2002). The incremental classifier can either request an additional feature or render a classification decision (Chai et al., 2004; Ji and Carin, 2007; Melville et al., 2005), choosing its actions to minimize a known cost function. Here, we assume that the *environment* chooses a feature, not the learner, as in some active learning settings (Settles, 2011). In Section 5, we use a MDP to decide whether additional features need to be processed in our application of incremental classification to a trivia game.

After losing a race for the Senate, this politician edited the Omaha World-Herald. This man resigned $^\diamond$ from one of his posts when the President sent a letter to Germany protesting the Lusitania $^\diamond$ sinking, and $^\diamond$ he advocated $^\diamond$ coining $^\diamond$ silver at a 16 $^\diamond$ to 1 $^{\diamond\diamond}$ rate $^\diamond$ compared to $^\diamond$ gold. He was the $^\diamond$ three-time Democratic $^\diamond$ Party $^{\diamond\diamond\diamond}$ nominee for $^\diamond$ President $^\diamond$ but $^{\diamond\diamond\diamond}$ lost to McKinley twice $^{\diamond\diamond}$ and then Taft, although he served as Secretary of State $^{\diamond\diamond}$ under Woodrow Wilson, $^\diamond$ and he later argued $^\diamond$ against Clarence Darrow $^\diamond$ in the Scopes $^{\diamond\diamond}$ Monkey Trial. For ten points, name this $^\diamond$ man who famously declared that "we shall not be crucified on a Cross of $^\diamond$ Gold". $^\diamond$

Figure 1: Quiz bowl question on William Jennings Bryan, a late nineteenth century American politician; obscure clues are at the beginning while more accessible clues are at the end. Words (excluding stop words) are shaded based on the number of times the word triggered a buzz from any player who answered the question (darker means more buzzes; buzzes contribute to the shading of the previous five words). Diamonds ($^\diamond$) indicate buzz positions.

2.1 Trivia as Incremental Classification

A real-life setting where humans classify documents incrementally is quiz bowl, an academic competition between schools in English-speaking countries; hundreds of teams compete in dozens of tournaments each year (Jennings, 2006). Note the distinction between quiz bowl and Jeopardy, a recent application area (Ferrucci et al., 2010). While Jeopardy also uses signaling devices, these are only usable *after a question is completed* (interrupting Jeopardy's questions would make for bad television). Thus, Jeopardy is *rapacious* classification followed by a race—among those who know the answer—to punch a button first.

Two teams listen to the same question.[3] In this context, a question is a series of clues (features) referring to the same entity (for an example question, see Figure 1). We assume a fixed feature ordering for a test sequence (i.e., you cannot request specific features). Teams interrupt the question at any point by "buzzing in"; if the answer is correct, the team gets points and the next question is read. Otherwise, the team loses points and the other team can answer.

The answers to quiz bowl questions are well-known entities (e.g., scientific laws, people, battles, books, characters, etc.), so the answer space is relatively limited; there are no open-ended questions of the form "why is the sky blue?" However, there are no multiple choice questions—as there are in Who Wants to Be a Millionaire (Lam et al., 2003)—or structural constraints—as there are in crossword puzzles (Littman et al., 2002).

Now that we introduced the concepts of questions, answers, and buzzes, we pause briefly to define them more formally and explicitly connect to machine learning. In the sequel, we will refer to: **questions**, sequences of words (tokens) associated with a single answer; **features**, inputs used for decisions (derived from the tokens in a question); **labels**, a question's correct response; **answers**, the responses (either correct or incorrect) provided; and **buzzes**, positions in a question where users halted the stream of features and gave an answer.

Quiz bowl is not a typical problem domain for natural language processing; why should we care about it? First, it is a real-world instance of incremental classification that happens hundreds of thousands of times most weekends. Second, it is a classification problem intricately intertwined with core computational linguistics problems such as anaphora resolution, online sentence processing, and semantic priming. Finally, quiz bowl's inherent fun makes it easy to acquire human responses, as we describe in the next section.

[3]Called a "starter" (UK) or "tossup" (US) in the lingo, as it often is followed by a "bonus" given to the team that answers the starter; here we only concern ourselves with tossups answerable by both teams.

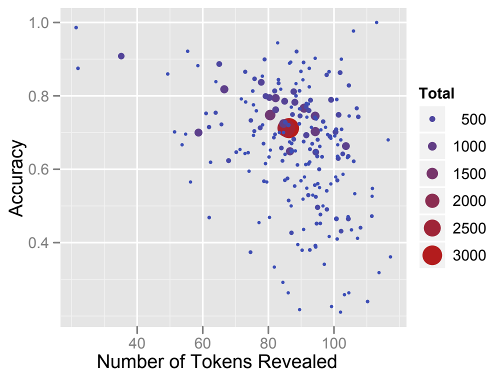
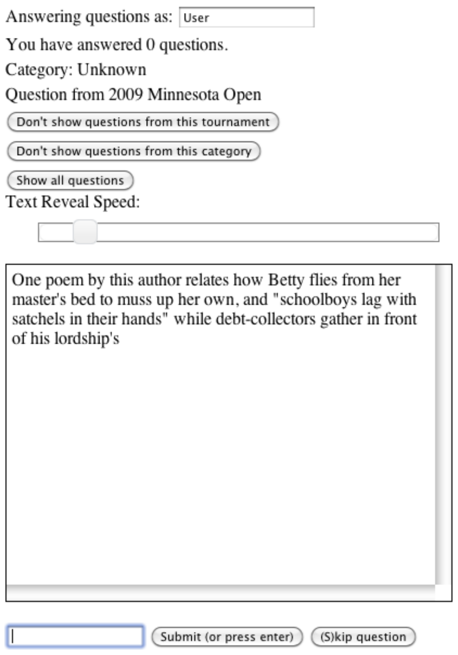


Figure 2: Users plotted based on *accuracy* vs. the *number of tokens*—on average—the user took to give an answer. Dot size and color represent the *total* number of questions answered. Users that answered questions later in the question had higher accuracy. However, there were users that were able to answer questions relatively early without sacrificing accuracy.


Answering questions as: User

You have answered 0 questions.

Category: Unknown

Question from 2009 Minnesota Open

Don't show questions from this tournament
Don't show questions from this category
Show all questions

Text Reveal Speed:

One poem by this author relates how Betty flies from her master's bed to muss up her own, and "schoolboys lag with satchels in their hands" while debt-collectors gather in front of his lordship's

Submit (or press enter)
(S)kip question

Figure 3: A screenshot of the webapp used to collect data. Users see a question revealed one word at a time. They signal buzzes by clicking on the answer button and input an answer.

3 Getting a Buzz through Crowdsourcing

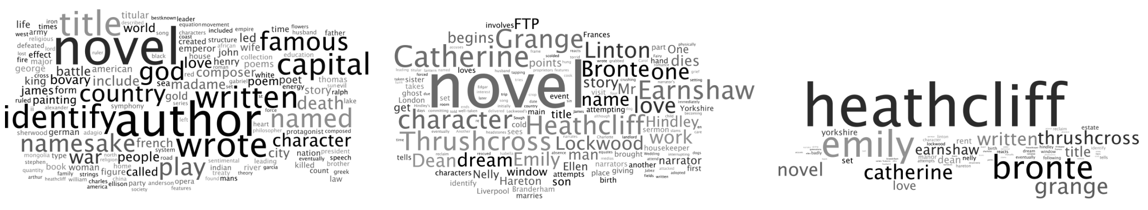
We built a corpus with 37,225 quiz bowl questions with 25,498 distinct labels from 121 tournaments written for tournaments between 1999 and 2010. We created a webapp[4] that simulates the experience of playing quiz bowl. Text is incrementally revealed (at a pace adjustable by the user) until users press the space bar to "buzz". Users then answer, and the webapp judges correctness using a string matching algorithm. Players can override the automatic check if the system mistakenly judged an answer incorrect. Answers of previous users are displayed after answering a question; this enhances the sense of community and keeps users honest (e.g., it's okay to say that "wj bryan" is an acceptable answer for the label "william jennings bryan", but "asdf" is not). We did not see examples of nonsense answers from malicious users; in contrast, users were stricter than we expected, perhaps because protesting required effort.

To collect a set of labels with many buzzes, we focused on the 1186 labels with more than four distinct questions. Thus, we shuffled the labels into a canonical order shown to all users (e.g., everyone saw a question on "Jonathan Swift" and then a question on "William Jennings Bryan", but because these labels have many questions the specific questions were different for each user). Participants were eager to answer questions; over 7000 questions were answered in the first day, and over 43000 questions were answered in two weeks by 461 users.

To represent a "buzz", we define a function $b(q, f)$ ("b" for buzz) as the number of times that feature f occurred in question q at most five tokens before a user correctly buzzed on that question.[5] Aggregating buzzes across questions (summing over q) shows different features useful for eliciting a buzz (Figure 4(a)). Some features coarsely identify the type of answer sought, e.g., "author", "opera", "city", "war", or "god". Other features are relational, connecting the answer to other clues, e.g., "namesake", "defeated", "husband", or "wrote". The set of buzzes help narrow which words are important for matching a question to its answer; for an example, see how the word cloud for all of the buzzes on "Wuthering Heights" (Figure 4(c)) is much more focused than the

[4]Play online or download the datasets at `http://umiacs.umd.edu/~jbg/qb`.

[5]This window was chosen qualitatively by examining the patterns of buzzes; this is person-dependent, based on reading comprehension, reaction time, and what reveal speed the user chose. We leave explicitly modeling this for future work.



(a) Buzzes over all Questions (b) Wuthering Heights Question Text (c) Buzzes on Wuthering Heights

Figure 4: Word clouds representing all words that were a part of a buzz (a), the original text appearing in seven questions on the book "Wuthering Heights" by Emily Brönte (b), and the buzzes of users on those questions (c). The buzzes reflect what users remember about the work and is more focused than the complete question text.

word cloud for *all* of the words from the questions with that label (Figure 4(b)).

4 Buzzes Reveal Useful Features

If we restrict ourselves to a finite set of labels, the process of answering questions is a multiclass classification problem. In this section, we show that information gleaned from humans making a similar decision can help improve rapacious machine learning classification. This validates that our crowdsourcing technique is gathering useful information.

We used a state-of-the-art maximum entropy classification model, MEGAM (Daumé III, 2004), that accepts a per-class mean prior for feature weights and applied MEGAM to the 200 most frequent labels (11,663 questions, a third of the dataset). The prior mean of the feature weight is a convenient, simple way to incorporate human feature utility; apart from the mean, all default options are used.

Specifying the prior requires us to specify a weight for each pair of label and feature. The weight combines buzz information (described in Section 3) and tf-idf (Salton, 1968). The tf-idf value is computed by treating the training set of questions with the same label as a single document.

Buzzes and tf-idf information were combined into the prior μ for label a and feature f as $\mu_{a,f} =$

$$\Big[\beta b(a,f) + \alpha \mathbb{I}\left[b(a,f) > 0\right] + \gamma\Big] \text{ tf-idf}(a,f). \quad (1)$$

We describe our weight strategies in increasing order of human knowledge. If α, β, and γ are zero, this is a naïve **zero** prior. If γ only is nonzero, this is a linear transformation of features' **tf-idf**. If only α is nonzero, this is a linear transformation of buzzed words' tf-idf weights. If only β is non-zero, *number* of buzzes is now a linear multiplier of the tf-idf weight (**buzz-linear**). Finally we allow unbuzzed words to have a separate linear transformation if both β and γ are non-zero (**buzz-tier**).

Weighting	α	β	γ	Error
zero	-	-	-	0.37
tf-idf	-	-	3.5	0.14
buzz-binary	7.1	-	-	0.10
buzz-linear	-	1.5	-	0.16
buzz-tier	-	1.1	0.1	**0.09**

Table 1: Classification error of a rapacious classifier able to draw on human incremental classification. The best weighting scheme for each dataset is in **bold**. Missing parameter values (-) mean that the parameter is fixed to zero for that weighting scheme.

Grid search (width of 0.1) on development set error was used to set parameters. Table 1 shows test error for weighting schemes and demonstrates that adding human information as a prior improves classification error, leading to a 36% error reduction over tf-idf alone. While not directly comparable (this classifier is rapacious, not incremental, and has a predefined answer space), the average user had an error rate of 16.7%.

5 Building an Incremental Classifier

In the previous section we improved rapacious classification using humans' incremental classification. A more interesting problem is how to compete against humans in incremental classification. While in the previous section we used human data for a *training* set, here we use human data as an *evaluation* set. Doing so requires us to formulate an incremental representation of the contents of questions and to learn a strategy to decide when to buzz.

Because this is the first machine learning algorithm for quiz bowl, we attempt to provide reasonable rapacious baselines and compare against our new strategies. We believe that our attempts represent a reasonable explanation of the problem space, but additional improvements could improve performance, as discussed in Section 8.

A common way to represent state-dependent strategies is via a Markov decision process (MDP). The most salient component of a MDP is the policy, a mapping from the state space to an action. In our context, a state is a sequence of (thus far revealed) tokens, and the action is whether to buzz or not. To learn a policy, we use a standard reinforcement learning technique (Langford and Zadrozny, 2005; Abbeel and Ng, 2004; Syed et al., 2008): given a representation of the state space, learn a classifier that can map from a state to an action. This is also a common paradigm for other incremental tasks, e.g., shift-reduce parsing (Nivre, 2008).

Given examples of the correct answer given a configuration of the state space, we can learn a MDP without explicitly representing the reward function. In this section, we define our method of defining actions and our representation of the state space.

5.1 Action Space

We assume that there are only two possible actions: buzz now or wait. An alternative would be a more expressive action space (e.g., an action for every possible answer). However, this conflates the question of *when* to buzz with *what* to answer. Instead, we call the distinct component that tells us *what to answer* the **content model**. We describe an initial content model in Section 5.2, below, and improve the models further in Section 7. For the moment, assume that a content model maintains a posterior distribution over labels and can at any time provide its best guess (e.g., given the features seen, the best answer is "William Jennings Bryan").

Given the action space, we need to specify where examples of state space and action come from. In the language of classification, we need to provide (x, y) pairs to learn a mapping $x \mapsto y$. The classifier attempts to learn that action y is ("buzz") in all states where the content model gave a correct response given state x. Negative examples ("wait") are applied to states where the content model gave a wrong answer. Every token in our training set corresponds to a classification example; both states are prevalent enough that we do not need to explicitly address class imbalance. In spirit, this setup resembles approaches that merge different classifiers (Riedel et al., 2011) or attempt to estimate confidence of models (Blatz et al., 2004).

This is a simplification of the problem and corresponds to a strategy of "buzz as soon as you know the answer", ignoring all other factors. While reasonable, this is not always optimal. For example, if you know your opponent is unlikely to answer a question, it is better to wait until you are more confident. Incorrect answers might also help your opponent, e.g., by eliminating an incorrect answer. Moreover, strategies in a game setting (rather than a single question) are more complicated. For example, sometimes you should not answer even if you know the correct answer.[6] Investigating such gameplay strategies would require a "roll out" of game states (Tesauro and Galperin, 1996); we leave this to future work.

We also investigated learning a policy directly from users' buzzes directly (Abbeel and Ng, 2004), but this performed poorly because the content model's incompatibility with players' abilities and the high variation in players' ability and styles (c.f., Figure 2).

5.2 State Space

Recall that our goal is to learn a classifier that maps states to actions; above, we defined the action space (the classifier's output) but not the state space, the classifier's input. The straightforward parameterization of the state space—all features that have been revealed is too sparse.

We use three components to form the state space: what information has been observed, what the content model believes is the correct answer, how confident the content model is, and whether the content model's confidence is changing. We describe each in more detail below.

Text In addition to the obvious, sparse parameterization that contains all (thus far) observed features, we also include the number of tokens revealed and whether the phrase "for ten points" has appeared.[7]

[6] If a right answer is worth $+10$ points and the penalty for an incorrect question is -5, then a team leading by 15 points on the last question should never attempt to answer.

[7] The phrase (abbreviated FTP) appears in all quiz bowl questions to signal the question's last sentence or clause. It is a signal

Guess An additional feature that we used to represent the state space is the current guess of the content model; i.e., the argmax of the posterior.

Posterior The posterior feature (**pos** for short) captures the shape of the posterior distribution: the probability of the current guess (the max of the posterior), the difference between the top two probabilities and the probabilities associated with the fifteen most probable labels under the posterior.

Change As features are revealed, there is often a rapid transition from a state of confusion—when there are many candidates with no clear best choice—to a state of clarity with the posterior pointing to only one probable label. To capture when this happens, we add a binary feature to reflect when the revelation of a single feature changes the content model's guess and a real-valued feature with the change in the maximum probability in the posterior.

Other Features We thought that other features would be useful. While useful on their own, no features that we tried were useful when the content model's **posterior** was also used as a feature. Features that we attempted to use were: a logistic regression model attempting to capture the probability that any player would answer (Silver et al., 2008), a regression predicting how many individuals would buzz in the next n words, the year the question was written, the category of the question, etc.

5.3 Naïve Content Model

The action space is only deciding *when* to answer, having abdicated responsibility for *what* to answer. So where does do the answers come from? We assume that at any point we can ask "what is the highest probability label given my current feature observations?" We call the component of our model that answers this question the *content model*.

Our first content model is a naïve Bayes model (Lewis, 1998) trained over a text collection. This generative model assumes labels for questions come from a multinomial distribution $\phi \sim \mathrm{Dir}(\alpha)$ and assumes that label l has a word distribution $\theta_l \sim \mathrm{Dir}(\lambda)$. Each question n has a label z_n and its words are generated from θ_{z_n}. Given labeled observations, we use the *maximum a posteriori* (MAP) estimate of θ_l.

Why use a generative model when a discriminative classifier could use a richer feature space? The most important reason is that, by definition, it makes sense to ask a generative model the probability of a label given a *partial* observation; such a question is not well-formed for discriminative models, which expect a complete feature set. Another important consideration is that generative models can predict future, unrevealed features (Chai et al., 2004); however, we do not make use of that capability here.

In addition to providing our answers, the content model also provides an additional, critically important feature for our state space: its **posterior** (**pos** for short) probability. With every revealed feature, the content model updates its posterior distribution over labels given that t tokens have been revealed in question n,

$$p(z_n \,|\, w_1 \ldots w_t, \phi, \boldsymbol{\theta}). \qquad (2)$$

To train our naïve Bayes model, we semi-automatically associate labels with a Wikipedia page (correcting mistakes manually) and then form the MAP estimate of the class multinomial distribution from the Wikipedia page's text. We did this for the 1065 labels that had at least three human answers, excluding ambiguous labels associated with multiple concepts (e.g., "europa", "steppenwolf", "georgia", "paris", and "v").

Features were taken to be the 25,000 most frequent tokens and bigrams[8] that were not stop words; features were extracted from the Wikipedia text in the same manner as from the question tokens.[9]

After demonstrating our ability to learn an incremental classifier using this simple content model, we extend the content model to capture local context and correlations between similar labels in Section 7.

to answer soon, as the final "giveaway" clue is next.

[8]We used NLTK (Loper and Bird, 2002) to filter stop words and we used a χ^2 test to identify bigrams with that rejected the null hypothesis at the 0.01 level.

[9]The Dirichlet scaling parameter λ was set to 10,000 given our relatively large vocabulary (25,000) and to not penalize a label's posterior probability if there were unseen features; this corresponds to a pseudocount of 0.4. α was set to 1.0.

6 Pitting the Algorithm Against Humans

With a state space and a policy, we now have all the necessary ingredients to have our algorithm compete against humans. Classification, which allows us to learn a policy, was done using the default settings of LIBLINEAR (Fan et al., 2008). To determine where the algorithm buzzes, we provide a sequence of state spaces until the policy classifier determines that it is time to buzz.

We simulate competition by taking the human answers and buzzes as a given and ask our algorithm (independently) to provide its decision on when to buzz on a test set. We compare the two buzz positions. If the algorithm buzzed earlier with the right answer, we consider it to have "won" the question; equivalently, if the algorithm buzzed later, we consider it to have "lost" that question. Ties are rare (less than 1% of cases), as the algorithm had significantly different behavior from humans; in the case where there was a tie, ties were broken in favor of the machine.

Because we have a large, diverse population answering questions, we need aggregate measures of human performance to get a comprehensive view of algorithm performance. We use the following metrics for each question in the test set:

- **best**: the earliest *anyone* buzzed correctly
- **median**: the first buzz after 50% of human buzzes
- **mean**: for each recorded buzz compute a reward and we average over all rewards

We compare the algorithm against baseline strategies:

- **rap** The rapacious strategy waits until the end of the question and answers the best answer possible.
- **ftp** Waiting until when "for 10 points" is said, then giving the best answer possible.
- **index**$_n$ Waiting until the first feature after the n^{th} token has been processed, then giving the best answer possible. The indices (30, 60, 90) were chosen to divide the typical question into four segments of equal length (by convention, most questions are of similar length).

We compare these baselines against policies that decide *when* to buzz based on the state.

Recall that the non-oracle algorithms were unaware of the true reward function. To best simulate conventional quiz bowl settings, a correct answer was $+10$ and the incorrect answer was -5. The full payoff matrix for the computer is shown in Table 2. Cases where the opponent buzzes first but is wrong are equivalent to rapacious classification, as there is no longer any incentive to answer early. Thus we exclude such situations (Outcomes 3, 5, 6 in Table 2) from the dataset to focus on the challenge of processing clues incrementally.

	Computer	Human	Payoff
1	first and wrong	right	-15
2	—	first and correct	-10
3	first and wrong	wrong	-5
4	first and correct	—	$+10$
5	wrong	first and wrong	$+5$
6	right	first and wrong	$+15$

Table 2: Payoff matrix (from the computer's perspective) for when agents "buzz" during a question. To focus on incremental classification, we exclude instances where the human interrupts with an *incorrect* answer, as after an opponent eliminates themselves, the answering reduces to rapacious classification.

Table 3 shows the algorithm did much better when it had access to features derived from the posterior. While incremental algorithms outperform rapacious baselines, they lose to humans. Against the median and average players, they lose between three and four points per question, and nearly twice that against the best players.

Although the content model is simple, this poor performance is not from the content model never producing the correct answer. To see this, we also computed the optimal actions that could be executed. We called this strategy the oracle strategy; it was able to consistently win against its opponents. Thus, while the content model was able to come up with correct answers often enough to on average win against opponents (even the best human players), we were unable to consistently learn winning policies.

There are two ways to solve this problem: create deeper, more nuanced policies (or the features that feed into them) or refine content models that provide the signal needed for our policies to make sound decisions. We chose to refine the content model, as we felt that we had tried all of the reasonable features that could help learn effective policies.

Strategy	Features	Mean	Best	Median	Index
Classify	text	-8.72	-10.04	-6.50	40.36
	+guess	-5.71	-8.40	-3.95	66.02
	+pos	-4.13	-7.56	-2.70	67.97
	+change	**-4.02**	**-7.41**	**-2.63**	77.33
Oracle	text	3.36	0.61	4.35	49.90
Rapacious Baseline	all	-6.61	-9.03	-4.42	100.19
	ftp	-5.22	-8.62	-4.23	88.65
	index$_{30}$	-7.89	-8.71	-6.41	32.23
	index$_{60}$	-5.16	**-7.56**	-3.71	61.90
	index$_{90}$	**-5.02**	-8.62	**-3.50**	87.13

Table 3: Performance of strategies against users. The human scoring columns show the average points per question (positive means winning on average, negative means losing on average) that the algorithm would expect to accumulate per question versus each human amalgam metric. The index column notes the average index of the token when the strategy chose to buzz.

7 Expanding the Content Model

When we asked quiz bowlers how they answer questions, they said that they first determine the category of a question, which substantially narrows the answer space. Ideally, the content model should conduct the same calculus—if a question seems to be about mathematics, all answers related with mathematics should be more likely in the posterior. This was consistent with our error analysis; many errors were nonsensical (e.g., answering "entropy" for "Johannes Brahms", when an answer such as "Robert Schumann", another composer, would be better).

In addition, assuming independence between features given a label causes us to ignore potentially informative multiword expressions such as quotations, titles, or dates. Adding a language model to our content model allows us to capture some of these phenomena.

To create a model that jointly models categories and local context, we propose the following model:

1. Draw a distribution over labels $\phi \sim \text{Dir}(\alpha)$
2. Draw a background distribution over words $\theta_0 \sim \text{Dir}(\lambda_0 \vec{1})$
   (a) For each category c of questions, draw a distribution over words $\theta_c \sim \text{Dir}(\lambda_1 \theta_0)$.
      i. For each label l in category c, draw a distribution over words $\theta_{l,c} \sim \text{Dir}(\lambda_2 \theta_c)$
         A. For each type v, draw a bigram distribution $\theta_{l,c,v} \sim \text{Dir}(\lambda_3 \theta_{l,c})$
3. Draw a distribution over labels $\phi \sim \text{Dir}(\alpha)$.
4. For each question with category c and N words, draw answer $l \sim \text{Mult}(\phi)$:
   (a) Assume $w_0 \equiv$ START
   (b) Draw $w_n \sim \text{Mult}(\theta_{l,c,w_{n-1}})$ for $n \in \{1 \ldots N\}$

This creates a language model over categories, labels, and observed words (we use "words" loosely, as bigrams replace some word pairs). By constructing the word distributions using hierarchical distributions based on domain and ngrams (a much simpler parametric version of more elaborate methods (Wood and Teh, 2009)), we can share statistical strength across related contexts. We assume that labels are (only) associated with their majority category as seen in our training data and that category assignments are observed. All scaling parameters λ were set to 10,000, α was 1.0, and the vocabulary was still 25,000.

We used the maximal seating assignment (Wallach, 2008) for propagating counts through the Dirichlet hierarchy. Thus, if the word v appeared $B_{l,u,v}$ times in label l following a preceding word u, $S_{l,v}$ times in label l, $T_{c,v}$ times in category c, and G_v times in total, we estimate the probability of a word v appearing in label k, category t, and after word u as $p(w_n = v \,|\, \text{lab} = l, \text{cat} = c, w_{n-1} = u; \vec{\lambda}) =$

$$\frac{B_{l,u,v} + \lambda_3 \frac{S_{l,v} + \lambda_2 \frac{T_{c,v} + \lambda_1 \frac{G_v + \lambda_0 / V}{G_{\cdot} + \lambda_0}}{T_{c,\cdot} + \lambda_2}}{S_{l,\cdot} + \lambda_2}}{B_{l,u,\cdot} + \lambda_3}, \quad (3)$$

where we use $\cdot$ to represent marginalization, e.g. $T_{c,\cdot} = \sum_{v'} T_{c,v'}$. As with naïve Bayes, Bayes' rule provides posterior label probabilities (Equation 2).

We compare the naïve model with models that capture more of the content in the text in Table 4; these results also include intermediate models between naïve Bayes and the full content model: "cat" (omit 2.a.i.A) and "bigram" (omit 2.a). These models perform much better than the naïve Bayes models seen in Table 3. They are about even against the mean and median players and lose four points per question against top players. However, there is still a substantial gap between our learned policies and the oracle. This suggests that better policies are possible.

7.1 Qualitative Analysis

In this section, we explore what defects are preventing the model presented here from competing with top players, exposing challenges in reinforcement learning, interpreting pragmatic cues, and large data.

Strategy	Model	Mean	Best	Median	Index
Classify	naïve	-4.02	-7.41	-2.63	77.33
	cat	-1.69	-5.22	0.12	67.97
	bigram	-3.80	-7.66	-2.51	78.69
	bgrm+cat	**-0.86**	**-4.46**	**0.83**	63.42
Oracle	naive	3.36	0.61	4.35	49.90
	cat	4.48	1.64	5.47	47.88
	bigram	3.58	0.87	4.61	49.34
	bgrm+cat	**4.67**	**1.99**	**5.74**	46.49

Table 4: As in Table 3, performance of strategies against users, but with enhanced content models. Modeling both bigrams and label categories improves overall performance.

Three examples of failures of the model are in Figure 5. This model is the best performing model of the previous section.

Too Slow The first example is a question on Maurice Ravel, a French composer known for *Boléro*. The question leads off with Ravel's orchestral version of Mussorgsky's piano piece "Pictures at an Exhibition". Based on that evidence, the algorithm considers "Pictures at an Exhibition" the most likely but does not yet buzz. When it receives enough information to be sure about the correct answer, over half of the players had already buzzed. Correcting this problem would require a more aggressive strategy, perhaps incorporating the identity of the opponent or estimating the difficulty of the question.

Mislead by the Content Model The second example is a question on Enrico Fermi, an Italian-American physicist. The first clues are about magnetic fields near a Fermi surface, which causes the content model to view "magnetic field" as the most likely answer. The question's text, however, has pragmatic cues "this man" and "this Italian" which would have ruled out the abstract answer "magnetic field". Correcting this would require a model that jointly models content and bigrams (Hardisty et al., 2010), has a coreference system as its content model (Haghighi and Klein, 2007), or determines the correct question type (Moldovan et al., 2000).

Insufficient Data The third example is where our approach had no chance. The question is a very difficult question about George Washington, America's first president. As a sign of its difficulty, only half the players answered correctly, and only near the end of the question. The question concerns lesser known

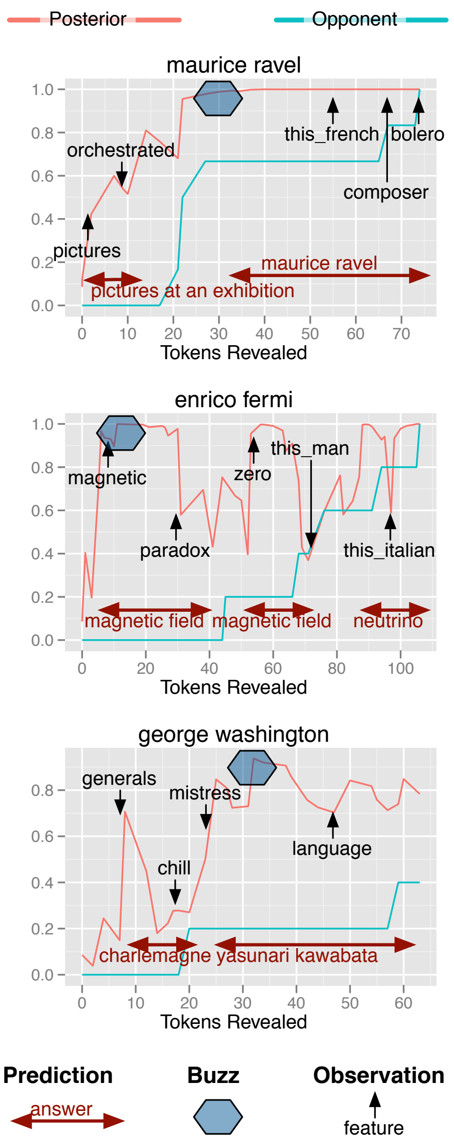


Figure 5: Three questions where our algorithm performed poorly. It gets "Maurice Ravel" (top) right but only after over half the humans had answered correctly (i.e., the buzz's hexagon appears when the cyan line is above 0.6); on "Enrico Fermi" (middle) it confuses the correct type of answer (person vs. concept); on "George Washington" (bottom) it lacks information to answer correctly. Lines represent the current estimate posterior probability of the answer (red) and the proportion of opponents who have answered the question correctly (cyan). The label of each of the three questions is above each chart. Words are in black with arrows and arrows, and the current argmax answer is at the bottom of the graph in red. The buzz location is the hexagon.

episodes from Washington's life, including a mistress caught in the elements. To the content model, of the several hypotheses it considers, the closest match it can find is "Yasunari Kawabata", who wrote the novel *Snow Country*, whose plot matches some of these keywords. To answer these types of question, the repository used to train the content model would have to be orders of magnitude larger to be able to link the disparate clues in the question to a consistent target. The content model would also benefit from weighting later (more informative) features higher.

7.2 Assumptions

We have made assumptions to solve a problem that is subtly different that the game of quiz bowl that a human would play. Some of these were simplifying assumptions, such as our assumption that the algorithm has a closed set of possible answers (Section 5.3). Even with this advantage, the algorithm is not always able to compete with human players, who choose answers from an unbounded set. On the other hand, to focus on incremental classification, we idealized our human opponents so that they never give incorrect answers (Section 6). This causes our estimates of our performance to be lower than they would be against real players. We hope to address both of these assumptions in the future.

8 Conclusion and Future Work

This paper makes three contributions. First, we introduced a new setting for exploring the problem of incremental classification: trivia games. This problem is intrinsically interesting because of its varied topics and competitive elements, has a great quantity of standardized, machine-readable data, and also has the boon of being cheaply and easily annotated. We took advantage of that ease and created a framework for quickly and efficiently gathering examples of humans doing incremental classification.

There are other potential uses for the dataset; the progression of clues from obscure nuggets to could help determine how "known" a particular aspect of an entity is (e.g., that William Jennings Bryant gave the "Cross of Gold" speech is better known his resignation after the Lusitania sinking, Figure 1). Which could be used in educational settings (Smith et al., 2008) or summarization (Das and Martins, 2007).

The second contribution shows that humans' incremental classification improves state-of-the-art rapacious classification algorithms. While other frameworks (Zaidan et al., 2008) have been proposed to incorporate user clues about features, the system described here provides analogous features without the need for explicit post-hoc reflection, has faster annotation throughput, and is much cheaper.

The problem of answering quiz bowl questions is itself a challenging task that combines issues from language modeling, large data, coreference, and reinforcement learning. While we do not address all of these problems, our third contribution is a system that learns a policy in a MDP for incremental classification even in very large state spaces; it can successfully compete with skilled human players.

Incorporating richer content models is one of our next steps. This would allow us to move beyond the closed-set model and use a more general coreference model (Haghighi and Klein, 2007) for identifying answers and broader corpora for training. In addition, using larger corpora would allow us to have more comprehensive doubly-hierarchical language models (Wood and Teh, 2009). We are also interested in adding richer models of opponents to the state space that would adaptively adjust strategies as it learned more about the strengths and weaknesses of its opponent (Waugh et al., 2011).

Further afield, our presentation of sentences closely resembles paradigms for cognitive experiments in linguistics (Thibadeau et al., 1982) but are much cheaper to conduct. If online processing effects (Levy et al., 2008; Levy, 2011) could be observed in buzzing behavior; e.g., if a confusingly worded phrase depresses buzzing probability, it could help validate cognitively-inspired models of online sentence processing.

Incremental classification is a natural problem, both for humans and resource-limited machines. While our data set is trivial (in a good sense), learning how humans process data and make decisions in a cheap, easy crowdsourced application can help us apply new algorithms to improve performance in settings where features aren't free, either because of computational or annotation cost.

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References

Pieter Abbeel and Andrew Y. Ng. 2004. Apprenticeship learning via inverse reinforcement learning. In *Proceedings of International Conference of Machine Learning*.

J. Blatz, E. Fitzgerald, G. Foster, S. Gandrabur, C. Goutte, A. Kulesza, A. Sanchis, and N. Ueffing. 2004. Confidence estimation for machine translation. In *Proceedings of the Association for Computational Linguistics*.

Mark Boddy and Thomas L. Dean. 1989. Solving time-dependent planning problems. In *International Joint Conference on Artificial Intelligence*, pages 979–984. Morgan Kaufmann Publishers, August.

Nicolò Cesa-Bianchi, Shai Shalev-Shwartz, and Ohad Shamir. 2011. Efficient learning with partially observed attributes. *Journal of Machine Learning Research*, 12:2857–2878.

Xiaoyong Chai, Lin Deng, Qiang Yang, and Charles X. Ling. 2004. Test-cost sensitive naive bayes classification. In *IEEE International Conference on Data Mining*.

Dipanjan Das and Andre Martins. 2007. A survey on automatic text summarization. *Engineering and Technology*, 4:192–195.

Hal Daumé III. 2004. Notes on CG and LM-BFGS optimization of logistic regression. Paper available at `http://pub.hal3.name/~daume04cg-bfgs`, implementation available at `http://hal3.name/megam/`.

Rong-En Fan, Kai-Wei Chang, Cho-Jui Hsieh, Xiang-Rui Wang, and Chih-Jen Lin. 2008. LIBLINEAR: A library for large linear classification. *Journal of Machine Learning Research*, 9:1871–1874.

David Ferrucci, Eric Brown, Jennifer Chu-Carroll, James Fan, David Gondek, Aditya A. Kalyanpur, Adam Lally, J. William Murdock, Eric Nyberg, John Prager, Nico Schlaefer, and Chris Welty. 2010. Building Watson: An Overview of the DeepQA Project. *AI Magazine*, 31(3).

Aria Haghighi and Dan Klein. 2007. Unsupervised coreference resolution in a nonparametric bayesian model. In *Proceedings of the Association for Computational Linguistics*.

Eric Hardisty, Jordan Boyd-Graber, and Philip Resnik. 2010. Modeling perspective using adaptor grammars. In *Proceedings of Emperical Methods in Natural Language Processing*.

Michael C. Horsch and David Poole. 1998. An anytime algorithm for decision making under uncertainty. In *Proceedings of Uncertainty in Artificial Intelligence*.

Ken Jennings. 2006. *Brainiac: adventures in the curious, competitive, compulsive world of trivia buffs*. Villard.

Shihao Ji and Lawrence Carin. 2007. Cost-sensitive feature acquisition and classification. *Pattern Recognition*, 40:1474–1485, May.

Shyong K. Lam, David M. Pennock, Dan Cosley, and Steve Lawrence. 2003. 1 billion pages = 1 million dollars? mining the web to play "who wants to be a millionaire?". In *Proceedings of Uncertainty in Artificial Intelligence*.

John Langford and Bianca Zadrozny. 2005. Relating reinforcement learning performance to classification performance. In *Proceedings of International Conference of Machine Learning*.

Roger P. Levy, Florencia Reali, and Thomas L. Griffiths. 2008. Modeling the effects of memory on human online sentence processing with particle filters. In *Proceedings of Advances in Neural Information Processing Systems*.

Roger Levy. 2011. Integrating surprisal and uncertain-input models in online sentence comprehension: formal techniques and empirical results. In *Proceedings of the Association for Computational Linguistics*.

David D. Lewis. 1998. Naive (Bayes) at forty: The independence assumption in information retrieval. In Claire Nédellec and Céline Rouveirol, editors, *Proceedings of European Conference of Machine Learning*, number 1398.

Michael L. Littman, Greg A. Keim, and Noam Shazeer. 2002. A probabilistic approach to solving crossword puzzles. *Artif. Intell.*, 134(1-2):23–55, January.

Edward Loper and Steven Bird. 2002. NLTK: the natural language toolkit. In *Tools and methodologies for teaching*.

Prem Melville, Maytal Saar-Tsechansky, Foster Provost, and Raymond J. Mooney. 2005. An expected utility approach to active feature-value acquisition. In *International Conference on Data Mining*, November.

Dan Moldovan, Sanda Harabagiu, Marius Pasca, Rada Mihalcea, Roxana Girju, Richard Goodrum, and Vasile

Rus. 2000. The structure and performance of an open-domain question answering system. In *Proceedings of the Association for Computational Linguistics*.

Joakim Nivre. 2008. Algorithms for deterministic incremental dependency parsing. *Comput. Linguist.*, 34(4):513–553, December.

Jay Pujara, Hal Daume III, and Lise Getoor. 2011. Using classifier cascades for scalable e-mail classification. In *Collaboration, Electronic Messaging, Anti-Abuse and Spam Conference*, ACM International Conference Proceedings Series.

Sebastian Riedel, David McClosky, Mihai Surdeanu, Andrew McCallum, and Christopher D. Manning. 2011. Model combination for event extraction in bionlp 2011. In *Proceedings of the BioNLP Workshop*.

Afshin Rostamizadeh, Alekh Agarwal, and Peter L. Bartlett. 2011. Learning with missing features. In *Proceedings of Uncertainty in Artificial Intelligence*.

Maytal Saar-Tsechansky and Foster Provost. 2007. Handling missing values when applying classification models. *Journal of Machine Learning Research*, 8:1623–1657, December.

Gerard. Salton. 1968. *Automatic Information Organization and Retrieval.* McGraw Hill Text.

Burr Settles. 2011. Closing the loop: Fast, interactive semi-supervised annotation with queries on features and instances. In *Proceedings of Emperical Methods in Natural Language Processing*.

David Silver, Richard S. Sutton, and Martin Müller. 2008. Sample-based learning and search with permanent and transient memories. In *International Conference on Machine Learning*.

Noah A. Smith, Michael Heilman, and Rebecca Hwa. 2008. Question generation as a competitive undergraduate course project. In *Proceedings of the NSF Workshop on the Question Generation Shared Task and Evaluation Challenge*.

Umar Syed, Michael Bowling, and Robert E. Schapire. 2008. Apprenticeship learning using linear programming. In *Proceedings of International Conference of Machine Learning*.

Gerald Tesauro and Gregory R. Galperin. 1996. On-line policy improvement using monte-carlo search. In *Proceedings of Advances in Neural Information Processing Systems*.

Robert Thibadeau, Marcel A. Just, and Patricia A. Carpenter. 1982. A model of the time course and content of reading. *Cognitive Science*, 6.

Hanna M Wallach. 2008. *Structured Topic Models for Language*. Ph.D. thesis, University of Cambridge.

Lidan Wang, Donald Metzler, and Jimmy Lin. 2010. Ranking Under Temporal Constraints. In *Proceedings of the ACM International Conference on Information and Knowledge Management*.

Kevin Waugh, Brian D. Ziebart, and J. Andrew Bagnell. 2011. Computational rationalization: The inverse equilibrium problem. In *Proceedings of International Conference of Machine Learning*.

F. Wood and Y. W. Teh. 2009. A hierarchical nonparametric Bayesian approach to statistical language model domain adaptation. In *Proceedings of Artificial Intelligence and Statistics*.

Omar F. Zaidan, Jason Eisner, and Christine Piatko. 2008. Machine learning with annotator rationales to reduce annotation cost. In *Proceedings of the NIPS*2008 Workshop on Cost Sensitive Learning*.

Valentina Bayer Zubek and Thomas G. Dietterich. 2002. Pruning improves heuristic search for cost-sensitive learning. In *International Conference on Machine Learning*.