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6
Watson on Jeopardy!: Unquestioned Answers from IBM's tour de force

It's been nearly a decade since IBM Watson crushed two puny humans on Jeopardy! Some people took that to mean that computers were definitively better than humans at trivia. But that isn't the complete answer—this chapter, inspired by Jeopardy!'s gimmick of responding to answers to questions, questions some of the "answers" that emerged from IBM's tour de force.

We begin the "modern" age of computer question answering and the rise of AI with *Watson*: an IBM-built AI that could play the American game show *Jeopardy!*

It's been over a decade since *Watson* appeared on TV, but it was revolutionary. This chapter will talk about how it changed my life, how it changed the way the public thought about AI, and how its technology paved the way for "modern" AI as exemplified by LLMs like GPT.

But this isn't a love letter to *Watson*. For all the fame and glory it won, the *Watson* story isn't without problems. Indeed, this chapter will make the argument that the game was subtly rigged in a way that set back research on AI.

6.1 Why IBM Chose Jeopardy! for a Grand Challenge

Watson is part of a long history of "grand challenge" projects meant to symbolize progress on AI. IBM (International Business Machines) is a New York-based technology company that for much of the twentieth century was synonymous with computing.

Grand Challenges

It had previously wowed the world by creating "Deep Blue", a chess-playing computer that defeated Gary Kasparov in 1997, widely considered the best chess player of the time (Hsu, 2002). Other AI grand challenges include those issued by funding agencies like the United States' Defense Advance Projecects Research Administration (DARPA) to build autonomous cars that can drive a hundred miles in the Mojave, although the best team just managed over seven miles (Patterson, 2005). Google/DeepMind had a similar ambition when they created AlphaGo, which like DeepBlue defeated Lee Sedol in 2016, widely considered the best Go player of the time (Koch, 2016).

The goal of these projects is not just to advance technology but to create a big enouch splash that people change how they think about technology.

It's hard to imagine an alternate world where these grand challenges did not happen, but I don't think it's exaggeration to say that these grand challenges did indeed change the world. After his defeat, Gary Kasparov took a "if you can't beat them, join them" approach and then began arguing for Centaur Chess: humans and computers playing chess together (this works for question answering too, as we discuss in Chapter 10.20). Likewise, the best Go players became more creative and novel moves by incorporating computer-like play into their play style **?**. And two decades after DARPA's autonomous grand challenge, we now have self-driving cars on the street in several US cities.

So what made IBM pick *Jeopardy!* for its grand challenge?

What Jeopardy! is and How it Works

Jeopardy! is a gameshow created by Merv Griffin that debuted in 1967 (Griffin, 2003). Its big gimmick is that the player responses are given in the form of a question in reaction to infamous human cheating scandals (we discuss how computers "cheat" in Chapter 10). For example, the clue

The CAPTCHA test against spam & robot programs is called the 'reverse' test named for this British code breaker

would have response Who is Alan Turing. The clues are arranged in a grid: columns represent categories and rows represent difficulty, with the more difficult questions being worth more.

There are three players who stand side by side behind podiums. When a clue is read, any of the three players can "buzz in" to say that they want to give a response. If they give the correct response, they then have "control of the board" and can select the next clue.

One advantage of controlling the board is that some questions are called "Daily Doubles" which allow the player to potentially double their score: a player can wager any part of their score, and if they get it right they get that ammount added to their score (but a wrong response will subtract it from their score).

How Watson changed my life

I remember when I first heard rumblings of Watson. Because I had a foot in both the AI and trivia communities, I heard two different stories. I heard rumors of amazing work in parsing and semantic role labeling happening from researchers who ventured north to Westchester county in New York (I was doing my PhD in New Jersey). From the trivia community, I heard of some people who were being paid by IBM to play trivia games but that they couldn't say anything more.

I was very sceptical. By the time that *Watson* came to fruition, I had moved to the University of Maryland. Then, my scepticism turned to jealousy. I watched, along with the rest of the world, one of the greatest achievements of AI unfold in front of me. What was I doing wasting my time working on language models if this was also legitimate research?

Let me be clear that the technical triumphs are indisputable (and, in my opinion, under-appreciated). From the work on wagering to synthesizing multiple information sources, Watson (Ferrucci et al., 2010) was from top to bottom a top-notch well-oiled machine. And it computed all of this in real time—something that wasn't strictly necessary but still impressive.

6.2 How Watson Works

While "neural" question answering (which we'll discuss in future chapter) is the big thing these days, Watson came of age in the *statistical* age. To understand some of how Watson works, its helpful to review some of the work that came before Watson that helped inspire it.

Rule-based Question Answering

Preceeding the statistical age of QA was the *rule-based* age: systems that were impressive on individual questions about baseball or geology but that faltered as soon as it saw a question that was unexpected in terms of the domain, they'd fail miserably.

One of the guiding principles of the statistical age was "the unreasonable effectiveness of big data", and this required scaling approaches to web-scale data. The first things that people tried was scaling up the "good, old-fashioned" approaches that defined the rule-based systems. Probably the most prominent system in this category is Start from Boris Katz at MIT. This system first launched in 1993. This, like many of the systems in this era, take an approach that's somewhat similar to to the old-fashioned AI approaches: parse the query with a and look it up in a knowledge base. For example, given the question:[1]

[1] This is an impressive/complicated question because David O. Selznick removed the first director (George Cukor) to replace him with Victor Fleming (the credited director), but Sam Wood had to fill in when Fleming collapsed on set.

Who directed *Gone with the Wind*?

Becomes the lookup

```
(get "imdb-movie" "Gone with the Wind (1939)" "DIRECTOR")
=> ("George Cukor" "Victor Fleming" "Sam Wood")
```
(Katz et al., 2002).

Some of these can be looked up directly in datasets, but START further builds on the systems like LUNAR and BASEBALL (Chapter 4.1). While those systems

LUNAR and BASEBALL also need to turn the raw text of questions into a structured representation, the difference of START is that is to deal with the messiness of Internet text. And its ability to *search* the Internet to find answers is clearly a huge influence on the subject of this chapter—*Watson*—and later Dense Passage Retrieval later (Chapter 9.1).

Transforming Questions to find the Answer

I n the next chapters about neural language models, we will discuss how new models *transform* questions into numbers (vectors) to find or generate the answer. But before we get there, it is useful to talk about how we can transform questions into text that can better find the answer. We begin with the Question Answering using Statistical Models (Radev et al., 2001, QASM).

One way of thinking about question answering is that it's a translation problem: questions are asked in one language but the answers are found in another language. QASM's approach is to explicitly "undo" the process to find the correct response given an input clue.

In Chapter 10.1, we'll talk about the cheating scandal around the American game show *21*, where Charles van Doren got the answers in advance. Part of the mythology of *Jeopardy!* is that Merv Griffen said, why don't we just give them the answers! So you have clues like

> During WWII this computer scientist & code breaker converted his money into silver & buried it; he never found his buried treasure.

The correct response, which is phrased as a question, is "Who is Alan Turing?" In other words, the central conceit of Jeopardy! is that it converts questions into answers (and then the contestants need to give a response to that answer in the form of a question).

What QASM is doing is doing the reverse: it has a model that tries to turn questions into the search string that could find the answer to the question (we'll see modern versions of this when we talk about multihop question answering in Chapter 7). QASM can apply plenty of transformations: swapping words, deleting words, ignoring words (e.g., if you have Cleveland, Ohio and ignore Ohio, you'll find more things about US president Grover Cleveland), etc.

In the end, you have a model that creates specialized queries from the original question. Later on, when we talk about dense passage retrieval, those systems are doing something similar, except they're generating the query in a continuous vector space (Chapter 9.1). Doing it with real words like QASM is more interpretable: a human could understand what's going on, while a vector query is inscrutable it seems to work better.

But how does this allow *Watson* to answer questions? When a question comes in, *Watson* searches over previous *Jeopardy!* questions, Wikipedia, articles, and a select subset of the Internet to find evidence that can answer the question.

Buzzing is important for Humans and Computers

Let's break this into two phases: **guessing** and **buzzing**. A guess is its best guess of what the answer could be: literally one of thousands of possible answers. A buzz is a binary decision of whether to trust whether this particular guess is correct or not.

Let's begin with an easy case: let's say you get a clue that's nearly identical to an existing clue:

DOUBLE D WORDS
Walk like a duck

Has appeared four times as a clue on *Jeopardy!*: 1987, 1996, 2001, and 2010. In addition to the above category, this clue also appeared under categories like **six-letter words** and **"WA"**. The guess process looks to see if it has ever seen this exactly clue before, it has, so it produces the guess waddle.

The buzzer needs to decide if it should trust this guess. It has a number that it associates with seeing the exact clue before; let's arbitrarily say that it's 3.0. It then compares that score with its threshold on when to buzz. Again, let's arbitrarily say that the threshold is 1.0. 3.0 is larger than 1.0, so it buzzes in with that guess (We'll talk more about how to set these numbers not-so-arbitrarily in Section 6.2).

But *Jeopardy!* doesn't have one kind of clue. There are many different types of question, and sometimes you get a clue from the category about what kind of question you will need to answer. Let's start with "potent potable rhyme time": from the name of the category, you know that both words in the response have to rhyme with each other and that it will have something to do with alchohol. So, to answer the clue:

Rice wine for the guy who rides a racehorse

, you are essentially doing a constrained search: you can find individual pieces that fit the clues (e.g., rewriting synonyms to discover things like makkoli, brem, tapai, etc. for "rice wine" and "cowboy" and "knight" for people who ride a horse). So your guesser would generate lots of different possibilities, but from past experience your buzzer would give a very low score to anything that didn't have two words. For example, if the category is "rhyme time" but there's only one word in the answer, the score goes down by 5.0, which balances out even if the buzzer likes sake by itself as a response. This is in essence a constrained search: you search for individual components that fit with the clue until you get two things that match the clue and then rhyme with each other.

Using Features

Now how does the buzzer know to use this information? There are many little pieces that could go into thinking that a guess is good or not. These pieces of evidences are called features. While features aren't always active, when they are, they provide evidence of whether a guess is good. For example, you could have a feature (and Watson probably did) for when a category has a "quote" in it: this means that the text inside the quote should appear in the answer. E.g., if you have a category `“Ten”-letter words`, then the clue

Patrick Roy and Hope Solo played this position

would have many possible answers that might score highly if you didn't take the category into account: e.g., goalie. But the category has two pieces of information: that the answer should be ten letters long: goalie fails that but goalkeeper does. However, the additional quoted part of the category tells the buzzer that it should give a low score to any guess that doesn't have "ten" in it.

In a computer programming language, this could simply be an if statement: if ASCII character 34 is in this string, return 1. But just knowing that there's a quote in the category does't tell you which clues to favor. You would need to make the the feature more specific.

Let's go to a question that I got while I was on Jeopardy! And this shows that these aren't just a category-specific phenomenon…this also apply to individual clues as well. In a quite normal category about geography, this clue came up:

"G.I." hope you know that 0 degrees latitude & 180 degrees longitude is just east of this group, part of Kiribati

Notice that "G.I." is in quotation marks. This is a signal that the correct response will start with G.I., in this case the correct response is "Gilbert[2] Islands". So perhaps we need to have multiple features to capture whether our answer is consistent with this clue. To be clear, we don't know exactly what features Watson used, but it could look something like this:

[2] Named of course for Johnny Gilbert, "the voice of *Jeopardy!*". Actually not, it's far more confusing than that: it was named by a German admiral—Adam Johann von Krusenstern—who led the first Russian circumnavigation of the globe. Krusenstern recognized that the British Captain Thomas Gilbert had described each of the islands individually and applied the the name to the group of islands.

- You might have one feature to indicate that there is a quotation mark in the clue.
- You could have another feature to show that the quote matches the candidate guess.
- Perhaps you have another feature that indicates whether the feature matches a multiword guess.

What made *Watson* such a *tour de force* is that humans had to come up with each of these features. This is not a one and done process. If you're building a system like this, you should look at things the system is still getting wrong and add a new feature to correct the issue. This is the same process that Watson used to build their statistical system. Maybe the system got confused when somebody has a quote from literature and you need to make sure that doesn't get counted or add a new feature to handle that case. It's very rare to get the features right the first time around.

The statistical approach has some advantages over the neural approach we'll see in the next chapter: it is easy to understand why a system is doing what it is. And it's easy to fix problems as they pop up.

In other cases, the constraint is that the correct answer starts with a particular letter.

The category that I feared the most was anagrams: where you need to rearrange the letters in the clue to get to the answer. This is actually easier for a computer than a human!

Each of these can have different approaches that can generate guesses that might be the correct answer. And you might think that this is all encoded in the category. Not so!

And for "normal" clues, this looks a lot like the reformulations that we saw in QASM: 400th anniversary of 1898 gets rewritten to 27th May 1498, India gets transformed into Kappad, and then you can find something with the correct response: Vasco de Gama.

So the first phase of the Watson pipeline is to—in parallel—generate all sorts of guesses based on different interpretations of the question. Some try to solve anagrams, others look for rhymes, others run an IR query like the Start system we talked about before, others are doing transformations like the QASM approach we talked about before.

And sometimes the approaches need to take a recursive approach, combining different subsystems to get to the right answer.

Logistic Regression and Gradient Descent

From this you have dozens of possible guesses. How do you know which—if any—to select? This all gets fed into a logistic regression problem. This can take into account how consistent the evidence matches the clue, how popular the response is, and it can even take into account things like Jeopardy!'s love of puns.

In the examples above, we assumed that we knew what the weights were for each of our features. For the moment, let's continue that assumption... but we'll try to improve them so that we get more buzzes right and fewer wrong. This will require a bit of math, so if you just want to jump ahead to the big picture (e.g., if you already know what SGD for logistic regression looks like), go ahead to Section 6.2.

So what does it mean to get more buzzes right? First, we need to define a little terminology: we need to consider the correct examples $\mathcal{X}_c$ and all the wrong examples $\mathcal{X}_f$. We want all of the correct examples to have scores more than the threshold and all of the incorrect examples to have scores less than the threshold. Let's call the threshold b, and then we need to sum up all of the non-zero features of an example to compute the score of an example i:

$$\text{score}(\boldsymbol{x}_i) = \sum_j w_j x_{i,j}. \tag{6.1}$$

In other words, we take every feature, multiply it by the weight associated with it (e.g., $x_{i,j}$ might be does this clue have a category with a quote in it). We write this as a multiplication and not as just adding the feature weights directly because sometimes our features won't be binary. And this should look familliar: it looks a lot like the dot product that we first saw in the chapter on information retrieval (Chapter 4), where we compute the *similarity* of two examples by multiplying the TF-IDF scores of two documents' words.

And this is a good segue to *why* we write this as a dot product rather than as a sum of all of the relevant feature weights. If all of the features of an example $x_{i,j}$ are binary, then you take the non-zero elements and add up the weights (since one times the weight just gives you the feature weights). But another very good feature might be how well the guess matches the clue (e.g., dot product between TF-IDF scores). So a way to generalize both the binary features and continuous features is to take the dot product of a vector representing all of the features and all of the weights to compute a score for the guess. The higher the score, the better the guess and the more likely the system will answer.

But this doesn't answer the question of how we can learn what the weights should be. We need to look at the cases where the system has generated a lot of guesses and seen which of them are correct or not. From this, you can learn that when a letter is in quotes and it matches, that's a good sign for getting a guess right. More concretely we want the score (Equation 6.1) to be high for right guesses and low for wrong ones, and if it's not, we need to adjust the scores by changing the weights $\boldsymbol{w}$.

One missing piece of the explanation is how to turn our weights into probabilities. For that, we are going to use the logistic function. This is a function that can take any real number as an input and turn it into a probability between zero and one. When the input is zero, it provides a probability is 0.5, and when the input goes to positive infinity, the probability approaches one; likewise, when the input goes to negative infinity, the probability approaches zero. For convenience, we will call this function $\sigma(x)$, because some people call this the sigmoid function.

For this, we are going to need an *objective function*: a mathematical expression that tells us how far we are from our goal. In this case our objective is to make the probability saying we should buzz—computed from our weights—for incorrect buzzes be as low as possible. So this means that we're going to transform our weights into a probability π_i between zero and one that gets

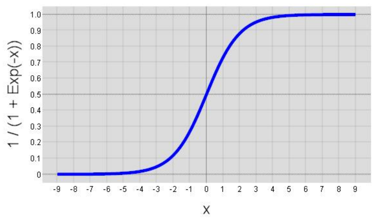


Figure 6.1: This function is called the sigmoid function because the way it transforms all inputs into values makes it look like an "S" shape, with 0 outputs to the left, increasing in the middle (an input of 0 right at the threshold gives an output of 0.5) and 1 outputs to the right.

big when the weights pass the threshold:

$$\pi_i = \sigma\left(\sum_j w_j x_{i,j} - b\right) \equiv p(\text{buzz} \mid \boldsymbol{x}) \equiv \frac{1}{1 + \exp - \left(\sum_j w_j x_{i,j} + b\right)}. \tag{6.2}$$

Since we only want to buzz when we're right, then we want π_i to be small (close to zero) whenever the buzz is wrong and big when the buzz is right (close to one). Alternatively, we could also say we want $1 - \pi_i$ to be big when the buzz is wrong, since this means that π_i is as close to zero. This alternate formulation is actually what we want since we will want to optimize a single function going in the same direction. Because we care about all examples, you would normally multiply the probability of joint events together, but this leads to a very small number (since probabilities are less than one), so for mathematical convenience we take the log:

$$\mathcal{L}' \equiv= \underbrace{\sum_{i \in \mathcal{X}_c} \log \pi_i}_{\text{How right are we}} + \underbrace{\sum_{i \in \mathcal{X}_f} \log 1 - \pi_i}_{\text{How wrong are we}}. \tag{6.3}$$

So this overall expression (the log probability) tells us how good of a job our features are doing in telling us when to buzz.

Later in the book, objective functions like this will be called a *loss function*, so to be consistent with that, we will think about how to *minimize our mistakes*, so what we will do now (somewhat confusingly) is to minimize the negative of $\mathcal{L}'$, which we will call $\mathcal{L}$:

$$\mathcal{L} \equiv= - \sum_{i \in \mathcal{X}_c} \log \pi_i - \sum_{i \in \mathcal{X}_f} \log 1 - \pi_i. \tag{6.4}$$

Just to recap: Equation 6.2 is the probability of the model saying we should buzz on example i, Equation 6.3 combines all of those together to see how close we are to being right, and then Equation 6.4 flips it around so that the large it is, the wronger we are... we want to minimize that expression.

If you remember high school calculus, this is an optimization problem: you can compute the derivative (gradient, actually) of each of each of the variables you have control over—the feature weights $\boldsymbol{w}$—and then adjust those weights to decrease the loss function represented by $\mathcal{L}$ (Equation 6.4). When you did this in high school calculus, you could probably solve the equation for when the derivative was zero, set the variable to make the derivative zero, and then you're done. But that's not possible here, so we need to take little adjustments to $\boldsymbol{w}$ to push $\mathcal{L}$ down again and again.

An intuitive way of thinking about this is that the shape of $\mathcal{L}$ represents a hill. Where you stand on the hill is represented by how you've set $\boldsymbol{w}$: each dimension represents one dimension of this vector.[3] In two dimensions, one dimension is how far north–south you are and one dimension is how far east–west you are: and you're trying to get to the lowest valley you can. The catch is that you can't really see what the whole landscape looks like; it's so foggy you can only see right around where you are. The intuition in this case is to walk "downhill", and this is exactly what the gradient of $\mathcal{L}$ gives you.

[3] The threshold b is also an additional dimension you need to optimize, but we'll gloss over this for now…you can always fudge it be imagining it an additional dimension of $\boldsymbol{w}$ that's always active for every example.

Now the problem is that computing $\mathcal{L}$ over your entire dataset is hard: you have to go over every single question in the *Jeopardy!* training set to compute its contribution to the gradient. The way that I like to think about it is that each example is a person you can ask "how do I go downhill". While you could ask lots of different people, if you ask literally everyone, that's probably going to be overkill. You can probably get a good sense of the direction by just asking a handful of example of which way you should go.

In the lingo, the sample of examples that you ask for the direction is the *minibatch*, and this overall process of asking a few (or even one) example for a direction is called *stochastic gradient descent* (Bottou, 2004).

Given that the math for the derivation is everywhere, I will skip it here (you can take a look at Chapter 5 of Speech and Language Processing by Jurafsky and Martin, which I often use in my classes and thus have adopted their notation), but it is so intuitive that if you look at it, it just "feels right". For a minibatch of size one, if you ask it which way you should go, it tells you to update[4] your weight w_i to be:

[4] Because we're doing stochastic *descent*, we subtract the gradient from the current weight…if we were trying to make the objective function as large as possible, we'd add it to the current weights.

$$w_j^{(new)} = w_j^{(old)} + \lambda \frac{\delta \mathcal{L}}{w_j} = w_j^{(old)} - \lambda \underbrace{(\pi_i - y_i)}_{\text{error}} x_{i,j}. \tag{6.5}$$

The most important part of the equation is the error: how far off your prediction for example j is. Remember that the true outcome y_i is binary (either you should have buzzed—$y_i = 1.0$—or you shouldn't have—$y_i = 0.0$), but that the prediction π_i is a probability and thus ranges between 0.0 and 1.0. The more right you are—the closer you are to y_i—the less the weights change. In other words, if you got this example exactly right, nothing changes at all. But the bigger your error is, the more you change. Exactly how much is controlled by the step size parameter λ, and the direction of the change depends on the sign of the error. If the error was positive, your prediction was too low, so you should increase all of the feature weights that caused you to say you should have buzzed when you didn't. If the error was negative, your prediction was too high, and so you slightly decrease all of the feature weights that caused you to get it wrong.

The other input to the update is how much of this feature the example has: $x_{i,j}$. To make sure your gradients don't get too big or too small, in practice we often standardize the feature weights so that they have mean zero and unit variance. However, because this chapter is trying explain how these things work (and we'll work through an example next), we won't do that to make the math more straightforward.

So let's see how this would work in a more real-world example. Let's say that you have a clue

US Cities

Its largest airport is named for a WWII hero.
Its second largest, for a WWII battle.

that Watson famously got wrong as a final *Jeopardy!* when it answered the famous American city Toronto. So in this case our buzzer input[5] is whether we should buzz on this clue with the response Toronto, for which we get a π_i. For the sake of concreteness, let's say π_i is 0.4…it's not high, but it *should* be zero because Midway and O'Hare airports are actually in the great city of Chicago. Now this is too high, so something went wrong with our features. Let's see what features were on and what their current weights in Table 6.1.

[5] In reality, the calculus for Final *Jeopardy!* is a little different because it makes sense to provide some answer no matter what, you don't really buzz in. However, you still want the best answer to have the highest probability, so we can still work through this example. And indeed, given the debugging output *Watson* wasn't very confident in its wrong output, so it probably wouldn't have "buzzed in" during normal play, suggesting that everything was working as intended. We talk about wagers at a cursory level in Section 6.4.

Feature	Weight w_i	x_i
IR Score	2	0.1
Toronto compatability with Category	1	0.2
Knowledge Base (# Airports in Toronto)	0.1	2
Previous responses (Toronto)	0.005	40
Bias	-0.8	

Table 6.1: Imagined features used in logistic regression for a wrong example.

These are reasonable features: the IR score encodes how similar this is to questions that you've seen before; the category feature encodes whether the answer is compatable with the category "US cities" (and while you imagine that it isn't great, you could imagine substituting "American" for "US", which would make Toronto a lot more plausible); the knowledge base feature checks to see how many airports are in Toronto; and the final feature checks to see if Toronto has been an answer before (you might imagine that more frequent answers in the past will appear again).

There are lots of other features that we're not seeing because they're zero, e.g., the feature that checks to see if there's a quotation mark in the category doesn't see one, so it's zero and we can safely ignore it along with every other feature that didn't fire.[6] And this makes sense: the features that aren't on for this feature had nothing to do with the mistake, so they shouldn't be punished or rewarded.

[6] Lest there be any doubt, I am making up these weights and features for a simple example… *Watson* had many more and better features. Most unbelievably, the first four features are non-zero for this example and the rest are zero. Finally, you normally don't have feature weights with such round numbers, but it makes the example cleaner.

First, lets see how these features translate into a probability:

$$\pi_i = \sigma\left(\underbrace{2 \cdot 0.1}_{\text{IR}} + \underbrace{1 \cdot 0.2}_{\text{Category}} + \underbrace{0.1 \cdot 2}_{\text{KB}} + \underbrace{0.005 \cdot 40}_{\text{Prev}} - \underbrace{0.8}_{\text{bias}}\right) \tag{6.6}$$

$$= \sigma\left(0.2 + 0.2 + 0.2 + 0.2 - 0.8\right) = \sigma\left(0.0\right) = 0.5 \tag{6.7}$$

From Equation 6.5, the error is 0.5—π_i should have been zero, but it was 0.5—and if we assume that our step size[7] is 1.0, we can now write the overall update

[7] In practice, this would be a really bad step size—it's way too large, you're likely to jump over the valley in the objective function you're looking for—but we'll go with this because it makes the math easier.

$$\boldsymbol{w}^{(new)} = \boldsymbol{w}^{(old)} - \lambda \nabla_{w,b} \mathcal{L} \tag{6.8}$$

$$= \begin{bmatrix} 2 \\ 1 \\ 0.1 \\ 0.005 \\ -0.8 \end{bmatrix} - \lambda \begin{bmatrix} \frac{\partial \mathcal{L}}{\partial w_1} \\ \frac{\partial \mathcal{L}}{\partial w_2} \\ \frac{\partial \mathcal{L}}{\partial w_3} \\ \frac{\partial \mathcal{L}}{\partial w_4} \\ \frac{\partial \mathcal{L}}{\partial b} \end{bmatrix} = \begin{bmatrix} 2 \\ 1 \\ 0.1 \\ 0.005 \\ -0.8 \end{bmatrix} - 1.0 \begin{bmatrix} 0.5 \cdot 0.1 \\ 0.5 \cdot 0.2 \\ 0.5 \cdot 2 \\ 0.5 \cdot 40 \\ 0.5 \cdot 1 \end{bmatrix} = \begin{bmatrix} 1.95 \\ 0.75 \\ -0.9 \\ -19.995 \\ -1.3 \end{bmatrix}.$$

This shows the dangers of having unbalanced feature weights and too large step sizes. This change is overall too big; you want to be taking little steps on your objective function, not taking huge leaps—you might jump over the "right answer" in front of you and not fix the real problem in this example: that Toronto is inconsistent with the category "US cities".

Feature Engineering

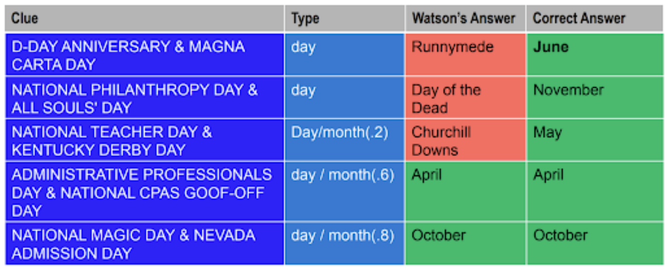
However, these updates can only update the features that you have. They cannot add new features nor can they fix problems intrinsic in the features. When you're starting out building a system like this, you usually don't have very many features. But as you go through the process of testing your initial system, you'll see lots things that your system gets wrong but *shouldn't*: your system has all of the evidence it needs to do what it needs, but cannot actually get there.

Let's focus on the Toronto question a little bit more. We already talked about how the feature itself might need some debugging (e.g., making sure that "US" doesn't expand to cover all of the American continent), but how could we add additional features that could handle this kind of phenomena better?

In a 2010 Tournament of Champions game, there was a category with the first clue:

CELEBRATIONS OF THE MONTH
D-Day anniversary and Magna Carta day

When the category was revealed, the host Alex Trebek said "you have to name the month", but *Watson* didn't get that hint. In a presentation from IBM, they showed that Watson got that clue wrong (Figure 6.2).



Clue	Type	Watson's Answer	Correct Answer
D-DAY ANNIVERSARY & MAGNA CARTA DAY	day	Runnymede	**June**
NATIONAL PHILANTHROPY DAY & ALL SOULS' DAY	day	Day of the Dead	November
NATIONAL TEACHER DAY & KENTUCKY DERBY DAY	Day/month(.2)	Churchill Downs	May
ADMINISTRATIVE PROFESSIONALS DAY & NATIONAL CPAS GOOF-OFF DAY	day / month(.6)	April	April
NATIONAL MAGIC DAY & NEVADA ADMISSION DAY	day / month(.8)	October	October

Figure 6.2: Slide from IBM *Watson* on how a feature to predict the answer type as it works it way through a category's column can improve its ability to buzz in correctly. (Figure Credit: IBM)

Something that is particularly unique to *Jeopardy!* and not to the other QA settings we've looked at is that the category (they text that appears atop the column a clue appears in) is a huge constraint on what the correct responses are. A large part of the Jeopardy! buzzer is figuring out the "lexical answer type": what kind of thing can the answer be and only buzzing in on the things that are consistent with that type. Part of this is is looking at clues in the clue. This chapter has used a lot of example clues like "this woman" (Sue Grafton), "this code breaker" (Turing), "this position" (goaltender), or "this group" (Gilbert Islands). These are hints about what kind of response is being sought. And lest you think this is an artifice of the skilled writers of *Jeopardy!*, this also appears in more "natural" questions like those people ask Google (Chapter 8.5).

And part of what made Watson a good *Jeopardy!* Player is that it would learn as it explored the category. After getting a couple of months wrong, Watson can learn that all of the answers should be a month. While we don't know for sure how this was implemented in detail, we can imagine that there is a feature that suggests whether the clue is consistent with an answer type of "day" or "month" (e.g., this clue is consistent with a "month" as an answer, and June is a month). And information from the current column could also be included in this, either directly in the computation of the feature or directly encoding something like "given the guess April, how many of the previous responses in the category are consistent with that type".

One thing that made *Watson* particularly groundbreaking was that it not just computed raw accuracy but also compared against human performance. This chart showed how Watson progressed in different iterations of the system, inching up to the cloud of *Jeopardy!* champions. Ken Jennings is in red there, still clearly dominating even the final version of Watson. This comparison is even more important today (Chapter 10) as people claim that AIs have super-human, but the lessons of *Watson* can help inform how we we can judge whether these judgements are fair and reasonable. So was the *Watson* match "the real deal"?

6.3 This Game is Rigged, I Tell Ya!

The nominal success of *Watson* has been well documented (not least by IBM itself, who rightly celebrated the great technical achievements and the great show they put on); however, things were not perfect…the game was rigged. It's useful to go over the lifecycle of an entire question: how it was written, how it's communicated, how players answer, and how the game unfolds afterward. At every stage, there's a slight benefit to the computer, which taken together makes this an unfair competition.

This is a problem! First, it's a problem scientifically because we want to have fair comparisons of human vs. computer intelligence. More importantly, I want to have my turn having my question answering robots sit opposite against trivia whizzes (Chapter 12), and I can't do that if everybody thinks that Watson's spin on *Jeopardy!* settled the issue (and it hasn't).

But first, in case you don't know how *Jeopardy!* works, we'll review that. However, if you've calculated a Coryat score before, you can go ahead and skip ahead to Section 6.3.

The Pool of Questions

Part of the agreement between *Jeopardy!* and IBM was that the competition would take place on normal, written questions. In the media coverage of the competition, this focused on avoiding video and picture daily doubles (fairly reasonable, but we'll discuss how multimedia questions might be more fun in Chapter 7.3). However, this causes two problems: the questions are too easy and do not necessarily challenge computers.

So what makes up "normal" questions? Every game of *Jeopardy!* has questions that range in difficulty. Because it's a television show, many questions are easy enough that the average viewer at home can get them. Moreover, the humans on the stage with Watson are not normal contestants. Ken Jennings is certifiably the greatest of all time (Low, 2020, GOAT) *Jeopardy!* player, and Brad Rutter isn't bad himself.

The average "normal" *Jeopardy!* contestant, including not so great players like yours truly, know a large majority of the clues. For top players like Brad and Ken, they know—with a handful of exceptions–*all* the clues. In a one-on-one fight with normal clues, Ken and Brad would be fighting over every clue: it would come down to who could buzz first.

This isn't fun to play. Nor is it fun to watch. This is why *Jeopardy!*'s tournament of champions is played on much more difficult[8] clues (Harris, 2006). Nonetheless, this is the battlefield where Watson won: "normal" questions that didn't challenge the human players. Instead, it all came down to the buzzer.

[8] The difficulty ratchet isn't one way; all "special" matches use designated questions: "Celebrity *Jeopardy!*" are easier (as mocked by categories like "States that end with Hampshire" or clues like "You wear these on your face to help you see better" on *Saturday Night Live*), and "College *Jeopardy!*" isn't necessarily easier but does have more college football and popular music. Questions are tuned to expected players' abilities. IBM did not want the computer to be targeted, lest the questions be adversarial against the computer. Chapter 10.19 discusses what this would look like if we specifically *wanted* that to happen.

John Henry vs. the Buzzing Machine

Unlike QB (Chapter 5.1), while *Jeopardy!* also uses signaling devices, these only work *once the question has been read in its entirety*; Ken Jennings (also a former QB player while he was a student at BYU) himself explains it on a *Planet Money* interview (Malone, 2019):

> **Jennings:** The buzzer is not live until Alex finishes reading the question. And if you buzz in before your buzzer goes live, *you actually lock yourself out for a fraction of a second.* So the big mistake on the show is people who are all adrenalized and are buzzing too quickly, too eagerly.
> **Malone:** OK. To some degree, *Jeopardy!* is kind of a video game, and a *crappy video game where it's, like, light goes on, press button*—that's it.
> **Jennings:** (Laughter) Yeah.

Jeopardy!'s buzzers are a gimmick to ensure good television; however, QB buzzers discriminate knowledge.

So how does this interact with Watson? Watson receives all of the clues electronically and likewise gets an electronic signal to know when it is safe to buzz in, then computes a probability of being right and buzzes in if it's above that threshold (Section 6.2). In contrast, humans have to either guess when it is safe to buzz or wait for a light to turn on.

Jeopardy! gurus explicitly advise new players not to wait for the light—your puny human reflexes are too slow. Indeed, one of Ken Jenning's strengths was his uncanny ability to internalize the cadence of Alex's voice and when a technitian would activate the buzzer (Jennings, 2006). In contrast, Watson is literally an electromechanical buzzing machine that could get first crack at every question it wants.[9]

[9] In practice, this is not always true. Because Watson computed its responses in real time, it could not come up with a response in time for particularly short questions.

Unfortunately, despite subjecting everyone within earshot to these rants, the computer science community thinks that the question is settled: computers are better than humans at answering questions. This is despite Ken basically saying that it did, indeed, come down to the buzzer.

Moreover, what makes for a "normal" difficulty question for a human does not always apply to a computer. Let's first talk about what makes a clue easier for a computer and then we'll talk about what makes a clue harder for a computer.

Easy for a Computer. When I appeared on *Jeopardy!*, my final *Jeopardy!* was:

> After this woman's death, her daughter wrote, "As far as we in the family are concerned, the alphabet now ends at Y"

All of us got the question right; it just so happened that *Jeopardy!* used a very similar clue that aired as we were recording:

“G” is for grand master as well as this woman who received the 2009 Grand Master Award.

The correct response is of course Sue Grafton. For poorly read contestant like myself, only studying previous clues allowed us to get the answer right. I’ve never read a Grafton book, but I know she writes mystery books and has titles of the form *“A” is for Alibi* (and that’s the only title I can think without looking at Wikipedia).

For Watson, this is “memorization” is trivial: a single letter implies that the answer is Grafton. But just like you should not think that I’m smart for getting lucky to have seen a reused clue, you should not praise Watson for finding near-repeat questions. And it’s not just trivia games: Google’s dataset of questions (which we’ll talk about in more Chapter 8.5) have many identical questions (Lewis et al., 2021), which makes it an imperfect yardstick. Moreover, Watson can also store the entirety of Wikipedia, easily looking up capitals, authors, etc.

Indeed, when a computer can find *an exact quote* (as was in my final *Jeopardy!* clue), the question becomes even easier. Then the computer just needs to find the appropriate article that contains the quote and then just find whatever entity is mostly likely to be a *Jeopardy!* answer.

Where systems like Watson struggle are on computation, matching novels and movies to plots, combining multiple clues, lateral thinking, and wordplay (Kaushik and Lipton, 2018). And this is not just a matter of degree: computers struggle with *all* such questions, even if they’re in the top row of *Jeopardy!* While a computer is theoretically good at math, the kinds of programs that answer trivia questions struggle answering match questions with numbers in the double digits (Wallace et al., 2019b).

This is why the goal of AI is *general* artificial intelligence (Chapter 3): while we can build specialized systems for *Jeopardy!* clues or math problems, unlike a reasonably smart human, a single program can’t “do it all”. Unlike for human contestants, the “difficulty” of *Jeopardy!* questions for a computer has no relationship to the nominal value. We talk about how Facebook/Meta dealt with this problem in Chapter 10.19: tell the authors what’s hard for a computer.

6.4 Two Nice Guys, One Computer with no Shame

Given the “too easy” questions and the buzzer, what does this actually mean for gameplay? A question comes in, and Watson has the choice of answering it or not: it can win every race to the buzzer if it wants. Then, of the things it cannot answer, Ken and Brad fight over the scraps. Thus, for a computer to win this competition, it needs only to be able to answer a third of the questions correctly.

Now, the *Jeopardy!* nerds reading the book (I love you all), will point out that this isn’t true, because the clues are not weighted equally: some are worth more than others. However, as we discussed above, what’s difficult for a computer isn't always difficult for a human (and *vice versa*), so it really is a random third of the questions. While a good human player might be weak on the buzzer and be confident that if they know more they'll win the harder clues, this isn't true for a human facing off against *Watson*.

Moreover, the computer has no shame: it uses a strategy called the "Forrest Bounce" (Rogak, 2020, more infamously associated with James Holzhauer and Arthur Chu). Rather than going through the categories top to bottom (easy to hard), Watson goes through the clues somewhat randomly, searching for Daily Doubles and trying to optimize its score. Again, there's nothing wrong with this—it's the optimal strategy! But if it's the "right" way to play the game, why doesn't every human do it?

That's because humans want to follow social norms. The producers of the show tell you up and down that you shouldn't play the game like that, and you don't want to make them unhappy with you... they can make your life miserable. I remember watching *Jeopardy!* with my grandmother and when someone hunted for the Daily Double, she would always say "who does he think he is" (and it was always a he). Alex Trebek also wasn't a fan (Marchese, 2018):[10]

> When the show's writers construct categories they do it so that there's a flow in terms of difficulty, and if you jump to the bottom of the category you may get a clue that would be easier to understand if you'd begun at the top of the category and saw how the clues worked. I like there to be order on the show, but as the impartial host I accept disorder.

[10] Rogak (2020) quotes a saltier take Trebek offered to Howard Stern: "It only works, dick-weed, if you know the correct response to everything that's up there."

And nobody, nobody, wants to make Alex unhappy.

Ken would sometimes do a little hunding for the Daily Double against a particularly formiddable opponent, but he would normally be well-behavied so as not to upset the powers that be. *Watson*, however, was a soulless machine; and having a machine on the stage was no exciting that nobody faulted it for its strategy. If anyone is to blame, it's probably Gary Tesauro; adding his strategy for playing the board increased Watson's win percentage considerably (Tesauro et al., 2013). But if you put him in a room with the withering stares of *Jeopardy!* producers (or worse, Alex Trebek) and that code would be deleted in no time.

6.5 *The Legacy of Watson*

Let's review Watson's appearance on *Jeopardy!*:

1. all questions are of "normal" difficulty;
2. thus the two human contestants know nearly all of the clues; but
3. Watson can win the buzzer race whenever it wants.

If Watson wins such a match, does that mean that it is superior to these supurb humans?

I hope that you are reluctant to answer "yes" (not just because *Jeopardy!* has trained you to respond to answers with questions). Perhaps I've planted a seed of doubt: *no, we cannot yet conclude computer superiority* from this experiment. And this is not the end of the story for judging whether computers are superhuman in their intelligence. Since then, we've seen claims that computers are smoking lawyers in taking the LSAT or is better than radiologists in reading X-rays. *Watson* was just the beginning of the story, as since then we've seen both a tremendous improvement in the technologies that drive AI (we review these advances in Chapter 9.1) and a greater interest in measuring how smart these models are. *Watson* was just the beginning of the story, in both respects.

In the next chapters, we go beyond the methods that *Watson* used to the modern QA has *actually* reached possible parity with humans and how to actually measure how far *ai* has come since Ken Jennings lost to *Watson* (Chapter 10).