9.4 **Duplicate URLs:** You have 10 billion URLs. How do you detect the duplicate documents? In this case, assume "duplicate" means that the URLs are identical.

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SOLUTION

Just how much space do 10 billion URLs take up? If each URL is an average of 100 characters, and each character is 4 bytes, then this list of 10 billion URLs will take up about 4 terabytes. We are probably not going to hold that much data in memory.

But, let's just pretend for a moment that we were miraculously holding this data in memory, since it's useful to first construct a solution for the simple version. Under this version of the problem, we would just create a hash table where each URL maps to `true` if it's already been found elsewhere in the list. (As an alternative solution, we could sort the list and look for the duplicate values that way. That will take a bunch of extra time and offers few advantages.)

Now that we have a solution for the simple version, what happens when we have all 4000 gigabytes of data and we can't store it all in memory? We could solve this either by storing some of the data on disk or by splitting up the data across machines.

Solution #1: Disk Storage

If we stored all the data on one machine, we would do two passes of the document. The first pass would split the list of URLs into 4000 chunks of 1 GB each. An easy way to do that might be to store each URL u in a file named `<x>.txt` where `x = hash(u) % 4000`. That is, we divide up the URLs based on their hash value (modulo the number of chunks). This way, all URLs with the same hash value would be in the same file.

In the second pass, we would essentially implement the simple solution we came up with earlier: load each file into memory, create a hash table of the URLs, and look for duplicates.

Solution #2: Multiple Machines

The other solution is to perform essentially the same procedure, but to use multiple machines. In this solution, rather than storing the data in file `<x>.txt`, we would send the URL to machine `x`.

Using multiple machines has pros and cons.

The main pro is that we can parallelize the operation, such that all 4000 chunks are processed simultaneously. For large amounts of data, this might result in a faster solution.

The disadvantage though is that we are now relying on 4000 different machines to operate perfectly. That may not be realistic (particularly with more data and more machines), and we'll need to start considering how to handle failure. Additionally, we have increased the complexity of the system simply by involving so many machines.

Both are good solutions, though, and both should be discussed with your interviewer.

9.5 **Cache:** Imagine a web server for a simplified search engine. This system has 100 machines to respond to search queries, which may then call out using `processSearch(string query)` to another cluster of machines to actually get the result. The machine which responds to a given query is chosen at random, so you cannot guarantee that the same machine will always respond to the same request. The method `processSearch` is very expensive. Design a caching mechanism to cache the results of the most recent queries. Be sure to explain how you would update the cache when data changes.

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SOLUTION

Before getting into the design of this system, we first have to understand what the question means. Many of the details are somewhat ambiguous, as is expected in questions like this. We will make reasonable assumptions for the purposes of this solution, but you should discuss these details—in depth—with your interviewer.

Assumptions

Here are a few of the assumptions we make for this solution. Depending on the design of your system and how you approach the problem, you may make other assumptions. Remember that while some approaches are better than others, there is no one "correct" approach.

- Other than calling out to `processSearch` as necessary, all query processing happens on the initial machine that was called.
- The number of queries we wish to cache is large (millions).
- Calling between machines is relatively quick.
- The result for a given query is an ordered list of URLs, each of which has an associated 50 character title and 200 character summary.
- The most popular queries are extremely popular, such that they would always appear in the cache.

Again, these aren't the *only* valid assumptions. This is just one reasonable set of assumptions.

System Requirements

When designing the cache, we know we'll need to support two primary functions:

- Efficient lookups given a key.
- Expiration of old data so that it can be replaced with new data.

In addition, we must also handle updating or clearing the cache when the results for a query change. Because some queries are very common and may permanently reside in the cache, we cannot just wait for the cache to naturally expire.

Step 1: Design a Cache for a Single System

A good way to approach this problem is to start by designing it for a single machine. So, how would you create a data structure that enables you to easily purge old data and also efficiently look up a value based on a key?

- A linked list would allow easy purging of old data, by moving "fresh" items to the front. We could implement it to remove the last element of the linked list when the list exceeds a certain size.

- A hash table allows efficient lookups of data, but it wouldn't ordinarily allow easy data purging.

How can we get the best of both worlds? By merging the two data structures. Here's how this works:

Just as before, we create a linked list where a node is moved to the front every time it's accessed. This way, the end of the linked list will always contain the stalest information.

In addition, we have a hash table that maps from a query to the corresponding node in the linked list. This allows us to not only efficiently return the cached results, but also to move the appropriate node to the front of the list, thereby updating its "freshness."

For illustrative purposes, abbreviated code for the cache is below. The code attachment provides the full code for this part. Note that in your interview, it is unlikely that you would be asked to write the full code for this as well as perform the design for the larger system.

```
public class Cache {
  public static int MAX_SIZE = 10;
  public Node head, tail;
  public HashMap<String, Node> map;
  public int size = 0;

  public Cache() {
    map = new HashMap<String, Node>();
  }

  /* Moves node to front of linked list */
  public void moveToFront(Node node) { ... }
  public void moveToFront(String query) { ... }

  /* Removes node from linked list */
  public void removeFromLinkedList(Node node) { ... }

  /* Gets results from cache, and updates linked list */
  public String[] getResults(String query) {
    if (!map.containsKey(query)) return null;

    Node node = map.get(query);
    moveToFront(node); // update freshness
    return node.results;
  }

  /* Inserts results into linked list and hash */
  public void insertResults(String query, String[] results) {
    if (map.containsKey(query)) { // update values
      Node node = map.get(query);
      node.results = results;
      moveToFront(node); // update freshness
      return;
    }

    Node node = new Node(query, results);
    moveToFront(node);
    map.put(query, node);

    if (size > MAX_SIZE) {
      map.remove(tail.query);
      removeFromLinkedList(tail);
    }
```

```
44     }
45 }
```

Step 2: Expand to Many Machines

Now that we understand how to design this for a single machine, we need to understand how we would design this when queries could be sent to many different machines. Recall from the problem statement that there's no guarantee that a particular query will be consistently sent to the same machine.

The first thing we need to decide is to what extent the cache is shared across machines. We have several options to consider.

Option 1: Each machine has its own cache.

A simple option is to give each machine its own cache. This means that if "`foo`" is sent to machine 1 twice in a short amount of time, the result would be recalled from the cache on the second time. But, if "`foo`" is sent first to machine 1 and then to machine 2, it would be treated as a totally fresh query both times.

This has the advantage of being relatively quick, since no machine-to-machine calls are used. The cache, unfortunately, is somewhat less effective as an optimization tool as many repeat queries would be treated as fresh queries.

Option 2: Each machine has a copy of the cache.

On the other extreme, we could give each machine a complete copy of the cache. When new items are added to the cache, they are sent to all machines. The entire data structure—linked list and hash table—would be duplicated.

This design means that common queries would nearly always be in the cache, as the cache is the same everywhere. The major drawback however is that updating the cache means firing off data to N different machines, where N is the size of the response cluster. Additionally, because each item effectively takes up N times as much space, our cache would hold much less data.

Option 3: Each machine stores a segment of the cache.

A third option is to divide up the cache, such that each machine holds a different part of it. Then, when machine `i` needs to look up the results for a query, machine `i` would figure out which machine holds this value, and then ask this other machine (machine `j`) to look up the query in `j`'s cache.

But how would machine `i` know which machine holds this part of the hash table?

One option is to assign queries based on the formula `hash(query) % N`. Then, machine `i` only needs to apply this formula to know that machine `j` should store the results for this query.

So, when a new query comes in to machine `i`, this machine would apply the formula and call out to machine `j`. Machine `j` would then return the value from its cache or call `processSearch(query)` to get the results. Machine `j` would update its cache and return the results back to `i`.

Alternatively, you could design the system such that machine `j` just returns `null` if it doesn't have the `query` in its current cache. This would require machine `i` to call `processSearch` and then forward the results to machine `j` for storage. This implementation actually increases the number of machine-to-machine calls, with few advantages.

Step 3: Updating results when contents change

Recall that some queries may be so popular that, with a sufficiently large cache, they would permanently be cached. We need some sort of mechanism to allow cached results to be refreshed, either periodically or "on-demand" when certain content changes.

To answer this question, we need to consider when results would change (and you need to discuss this with your interviewer). The primary times would be when:

1. The content at a URL changes (or the page at that URL is removed).
2. The ordering of results change in response to the rank of a page changing.
3. New pages appear related to a particular query.

To handle situations #1 and #2, we could create a separate hash table that would tell us which cached queries are tied to a specific URL. This could be handled completely separately from the other caches, and reside on different machines. However, this solution may require a lot of data.

Alternatively, if the data doesn't require instant refreshing (which it probably doesn't), we could periodically crawl through the cache stored on each machine to purge queries tied to the updated URLs.

Situation #3 is substantially more difficult to handle. We could update single word queries by parsing the content at the new URL and purging these one-word queries from the caches. But, this will only handle the one-word queries.

A good way to handle Situation #3 (and likely something we'd want to do anyway) is to implement an "automatic time-out" on the cache. That is, we'd impose a time out where *no* query, regardless of how popular it is, can sit in the cache for more than `x` minutes. This will ensure that all data is periodically refreshed.

Step 4: Further Enhancements

There are a number of improvements and tweaks you could make to this design depending on the assumptions you make and the situations you optimize for.

One such optimization is to better support the situation where some queries are very popular. For example, suppose (as an extreme example) a particular string constitutes 1% of all queries. Rather than machine `i` forwarding the request to machine `j` every time, machine `i` could forward the request just once to `j`, and then `i` could store the results in its own cache as well.

Alternatively, there may also be some possibility of doing some sort of re-architecture of the system to assign queries to machines based on their hash value (and therefore the location of the cache), rather than randomly. However, this decision may come with its own set of trade-offs.

Another optimization we could make is to the "automatic time out" mechanism. As initially described, this mechanism purges any data after `X` minutes. However, we may want to update some data (like current news) much more frequently than other data (like historical stock prices). We could implement timeouts based on topic or based on URLs. In the latter situation, each URL would have a time out value based on how frequently the page has been updated in the past. The time out for the query would be the minimum of the time outs for each URL.

These are just a few of the enhancements we can make. Remember that in questions like this, there is no single correct way to solve the problem. These questions are about having a discussion with your interviewer about design criteria and demonstrating your general approach and methodology.

9.6 **Sales Rank**: A large eCommerce company wishes to list the best-selling products, overall and by category. For example, one product might be the #1056th best-selling product overall but the #13th best-selling product under "Sports Equipment" and the #24th best-selling product under "Safety." Describe how you would design this system.

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SOLUTION

Let's first start off by making some assumptions to define the problem.

Step 1: Scope the Problem

First, we need to define what exactly we're building.

- We'll assume that we're only being asked to design the components relevant to this question, and not the entire eCommerce system. In this case, we might touch the design of the frontend and purchase components, but only as it impacts the sales rank.
- We should also define what the sales rank means. Is it total sales over all time? Sales in the last month? Last week? Or some more complicated function (such as one involving some sort of exponential decay of sales data)? This would be something to discuss with your interviewer. We will assume that it is simply the total sales over the past week.
- We will assume that each product can be in multiple categories, and that there is no concept of "subcategories."

This part just gives us a good idea of what the problem, or scope of features, is.

Step 2: Make Reasonable Assumptions

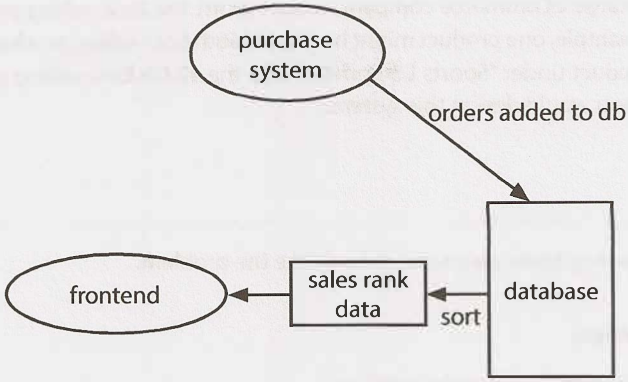
These are the sorts of things you'd want to discuss with your interviewer. Because we don't have an interviewer in front of us, we'll have to make some assumptions.

- We will assume that the stats do not need to be 100% up-to-date. Data can be up to an hour old for the most popular items (for example, top 100 in each category), and up to one day old for the less popular items. That is, few people would care if the #2,809,132th best-selling item should have actually been listed as #2,789,158th instead.
- Precision is important for the most popular items, but a small degree of error is okay for the less popular items.
- We will assume that the data should be updated every hour (for the most popular items), but the time range for this data does not need to be precisely the last seven days (168 hours). If it's sometimes more like 150 hours, that's okay.
- We will assume that the categorizations are based strictly on the origin of the transaction (i.e., the seller's name), not the price or date.

The important thing is not so much which decision you made at each possible issue, but whether it occurred to you that these are assumptions. We should get out as many of these assumptions as possible in the beginning. It's possible you will need to make other assumptions along the way.

Step 3: Draw the Major Components

We should now design just a basic, naive system that describes the major components. This is where you would go up to a whiteboard.



In this simple design, we store every order as soon as it comes into the database. Every hour or so, we pull sales data from the database by category, compute the total sales, sort it, and store it in some sort of sales rank data cache (which is probably held in memory). The frontend just pulls the sales rank from this table, rather than hitting the standard database and doing its own analytics.

Step 4: Identify the Key Issues

Analytics are Expensive

In the naive system, we periodically query the database for the number of sales in the past week for each product. This will be fairly expensive. That's running a query over all sales for all time.

Our database just needs to track the total sales. We'll assume (as noted in the beginning of the solution) that the general storage for purchase history is taken care of in other parts of the system, and we just need to focus on the sales data analytics.

Instead of listing every purchase in our database, we'll store just the total sales from the last week. Each purchase will just update the total weekly sales.

Tracking the total sales takes a bit of thought. If we just use a single column to track the total sales over the past week, then we'll need to re-compute the total sales every day (since the specific days covered in the last seven days change with each day). That is unnecessarily expensive.

Instead, we'll just use a table like this.

Prod ID	Total	Sun	Mon	Tues	Wed	Thurs	Fri	Sat

This is essentially like a circular array. Each day, we clear out the corresponding day of the week. On each purchase, we update the total sales count for that product on that day of the week, as well as the total count.

We will also need a separate table to store the associations of product IDs and categories.

Prod ID	Category ID

To get the sales rank per category, we'll need to join these tables.

Database Writes are Very Frequent

Even with this change, we'll still be hitting the database very frequently. With the amount of purchases that could come in every second, we'll probably want to batch up the database writes.

Instead of immediately committing each purchase to the database, we could store purchases in some sort of in-memory cache (as well as to a log file as a backup). Periodically, we'll process the log / cache data, gather the totals, and update the database.

> We should quickly think about whether or not it's feasible to hold this in memory. If there are 10 million products in the system, can we store each (along with a count) in a hash table? Yes. If each product ID is four bytes (which is big enough to hold up to 4 billion unique IDs) and each count is four bytes (more than enough), then such a hash table would only take about 40 megabytes. Even with some additional overhead and substantial system growth, we would still be able to fit this all in memory.

After updating the database, we can re-run the sales rank data.

We need to be a bit careful here, though. If we process one product's logs before another's, and re-run the stats in between, we could create a bias in the data (since we're including a larger timespan for one product than its "competing" product).

We can resolve this by either ensuring that the sales rank doesn't run until all the stored data is processed (difficult to do when more and more purchases are coming in), or by dividing up the in-memory cache by some time period. If we update the database for all the stored data up to a particular moment in time, this ensures that the database will not have biases.

Joins are Expensive

We have potentially tens of thousands of product categories. For each category, we'll need to first pull the data for its items (possibly through an expensive join) and then sort those.

Alternatively, we could just do one join of products and categories, such that each product will be listed once per category. Then, if we sorted that on category and then product ID, we could just walk the results to get the sales rank for each category.

Prod ID	Category	Total	Sun	Mon	Tues	Wed	Thurs	Fri	Sat
1423	sportseq	13	4	1	4	19	322	32	232
1423	safety	13	4	1	4	19	322	32	232

Rather than running thousands of queries (one for each category), we could sort the data on the category first and then the sales volume. Then, if we walked those results, we would get the sales rank for each category. We would also need to do one sort of the entire table on just sales number, to get the overall rank.

We could also just keep the data in a table like this from the beginning, rather than doing joins. This would require us to update multiple rows for each product.

Database Queries Might Still Be Expensive

Alternatively, if the queries and writes get very expensive, we could consider forgoing a database entirely and just using log files. This would allow us to take advantage of something like MapReduce.

Under this system, we would write a purchase to a simple text file with the product ID and time stamp. Each category has its own directory, and each purchase gets written to all the categories associated with that product.

We would run frequent jobs to merge files together by product ID and time ranges, so that eventually all purchases in a given day (or possibly hour) were grouped together.

```
/sportsequipment
    1423,Dec 13 08:23-Dec 13 08:23,1
    4221,Dec 13 15:22-Dec 15 15:45,5
    ...
/safety
    1423,Dec 13 08:23-Dec 13 08:23,1
    5221,Dec 12 03:19-Dec 12 03:28,19
...
```

To get the best-selling products within each category, we just need to sort each directory.

How do we get the overall ranking? There are two good approaches:

- We could treat the general category as just another directory, and write every purchase to that directory. That would mean a lot of files in this directory.
- Or, since we'll already have the products sorted by sales volume order for each category, we can also do an N-way merge to get the overall rank.

Alternatively, we can take advantage of the fact that the data doesn't need (as we assumed earlier) to be 100% up-to-date. We just need the most popular items to be up-to-date.

We can merge the most popular items from each category in a pairwise fashion. So, two categories get paired together and we merge the most popular items (the first 100 or so). After we have 100 items in this sorted order, we stop merging this pair and move onto the next pair.

To get the ranking for all products, we can be much lazier and only run this work once a day.

One of the advantages of this is that it scales nicely. We can easily divide up the files across multiple servers, as they aren't dependent on each other.

Follow Up Questions

The interviewer could push this design in any number of directions.

- Where do you think you'd hit the next bottlenecks? What would you do about that?
- What if there were subcategories as well? So items could be listed under "Sports" and "Sports Equipment" (or even "Sports" > "Sports Equipment" > "Tennis" > "Rackets")?
- What if data needed to be more accurate? What if it needed to be accurate within 30 minutes for all products?

Think through your design carefully and analyze it for the tradeoffs. You might also be asked to go into more detail on any specific aspect of the product.

9.7 **Personal Financial Manager**: Explain how you would design a personal financial manager (like Mint.com). This system would connect to your bank accounts, analyze your spending habits, and make recommendations.

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SOLUTION

The first thing we need to do is define what it is exactly that we are building.

Step 1: Scope the Problem

Ordinarily, you would clarify this system with your interviewer. We'll scope the problem as follows:

- You create an account and add your bank accounts. You can add multiple bank accounts. You can also add them at a later point in time.
- It pulls in all your financial history, or as much of it as your bank will allow.
- This financial history includes outgoing money (things you bought or paid for), incoming money (salary and other payments), and your current money (what's in your bank account and investments).
- Each payment transaction has a "category" associated with it (food, travel, clothing, etc.).
- There is some sort of data source provided that tells the system, with some reliability, which category a transaction is associated with. The user might, in some cases, override the category when it's improperly assigned (e.g., eating at the cafe of a department store getting assigned to "clothing" rather than "food").
- Users will use the system to get recommendations on their spending. These recommendations will come from a mix of "typical" users ("people generally shouldn't spend more than X% of their income on clothing"), but can be overridden with custom budgets. This will not be a primary focus right now.
- We assume this is just a website for now, although we could potentially talk about a mobile app as well.
- We probably want email notifications either on a regular basis, or on certain conditions (spending over a certain threshold, hitting a budget max, etc.).
- We'll assume that there's no concept of user-specified rules for assigning categories to transactions.

This gives us a basic goal for what we want to build.

Step 2: Make Reasonable Assumptions

Now that we have the basic goal for the system, we should define some further assumptions about the characteristics of the system.

- Adding or removing bank accounts is relatively unusual.
- The system is write-heavy. A typical user may make several new transactions daily, although few users would access the website more than once a week. In fact, for many users, their primary interaction might be through email alerts.
- Once a transaction is assigned to a category, it will only be changed if the user asks to change it. The system will never reassign a transaction to a different category "behind the scenes", even if the rules change. This means that two otherwise identical transactions could be assigned to different categories if the rules changed in between each transaction's date. We do this because it may confuse users if their spending per category changes with no action on their part.
- The banks probably won't push data to our system. Instead, we will need to pull data from the banks.
- Alerts on users exceeding budgets probably do not need to be sent instantaneously. (That wouldn't be realistic anyway, since we won't get the transaction data instantaneously.) It's probably pretty safe for them to be up to 24 hours delayed.

It's okay to make different assumptions here, but you should explicitly state them to your interviewer.