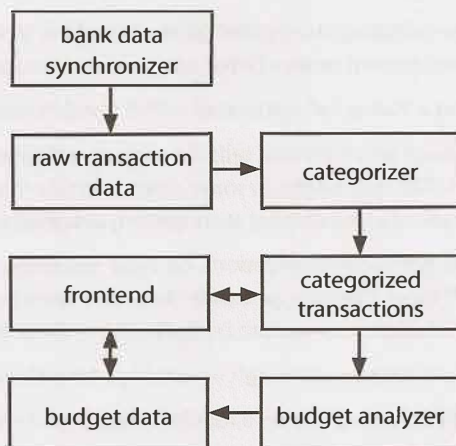


Step 3: Draw the Major Components

The most naive system would be one that pulls bank data on each login, categorizes all the data, and then analyzes the user's budget. This wouldn't quite fit the requirements, though, as we want email notifications on particular events.

We can do a bit better.



With this basic architecture, the bank data is pulled at periodic times (hourly or daily). The frequency may depend on the behavior of the users. Less active users may have their accounts checked less frequently.

Once new data arrives, it is stored in some list of raw, unprocessed transactions. This data is then pushed to the categorizer, which assigns each transaction to a category and stores these categorized transactions in another datastore.

The budget analyzer pulls in the categorized transactions, updates each user's budget per category, and stores the user's budget.

The frontend pulls data from both the categorized transactions datastore as well as from the budget datastore. Additionally, a user could also interact with the frontend by changing the budget or the categorization of their transactions.

Step 4: Identify the Key Issues

We should now reflect on what the major issues here might be.

This will be a very data-heavy system. We want it to feel snappy and responsive, though, so we'll want as much processing as possible to be asynchronous.

We will almost certainly want at least one task queue, where we can queue up work that needs to be done. This work will include tasks such as pulling in new bank data, re-analyzing budgets, and categorizing new bank data. It would also include re-trying tasks that failed.

These tasks will likely have some sort of priority associated with them, as some need to be performed more often than others. We want to build a task queue system that can prioritize some task types over others, while still ensuring that all tasks will be performed eventually. That is, we wouldn't want a low priority task to essentially "starve" because there are always higher priority tasks.

One important part of the system that we haven't yet addressed will be the email system. We could use a task to regularly crawl user's data to check if they're exceeding their budget, but that means checking every

single user daily. Instead, we'll want to queue a task whenever a transaction occurs that potentially exceeds a budget. We can store the current budget totals by category to make it easy to understand if a new transaction exceeds the budget.

We should also consider incorporating the knowledge (or assumption) that a system like this will probably have a large number of inactive users—users who signed up once and then haven't touched the system since. We may want to either remove them from the system entirely or deprioritize their accounts. We'll want some system to track their account activity and associate priority with their accounts.

The biggest bottleneck in our system will likely be the massive amount of data that needs to be pulled and analyzed. We should be able to fetch the bank data asynchronously and run these tasks across many servers. We should drill a bit deeper into how the categorizer and budget analyzer work.

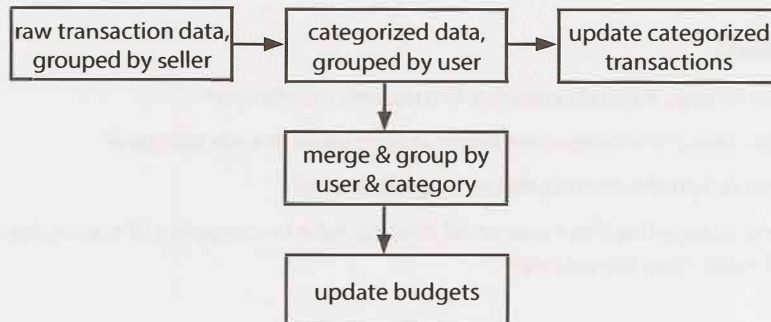
Categorizer and Budget Analyzer

One thing to note is that transactions are not dependent on each other. As soon as we get a transaction for a user, we can categorize it and integrate this data. It might be inefficient to do so, but it won't cause any inaccuracies.

Should we use a standard database for this? With lots of transactions coming in at once, that might not be very efficient. We certainly don't want to do a bunch of joins.

It may be better instead to just store the transactions to a set of flat text files. We assumed earlier that the categorizations are based on the seller's name alone. If we're assuming a lot of users, then there will be a lot of duplicates across the sellers. If we group the transaction files by seller's name, we can take advantage of these duplicates.

The categorizer can do something like this:



It first gets the raw transaction data, grouped by seller. It picks the appropriate category for the seller (which might be stored in a cache for the most common sellers), and then applies that category to all those transactions.

After applying the category, it re-groups all the transactions by user. Then, those transactions are inserted into the datastore for this user.

before categorizer	after categorizer
amazon/ user121,\$5.43,Aug 13 user922,\$15.39,Aug 27 ...	user121/ amazon,shopping,\$5.43,Aug 13 ...
comcast/ user922,\$9.29,Aug 24 user248,\$40.13,Aug 18 ...	user922/ amazon,shopping,\$15.39,Aug 27 comcast,utilities,\$9.29,Aug 24 ...
	user248/ comcast,utilities,\$40.13,Aug 18 ...

Then, the budget analyzer comes in. It takes the data grouped by user, merges it across categories (so all Shopping tasks for this user in this timespan are merged), and then updates the budget.

Most of these tasks will be handled in simple log files. Only the final data (the categorized transactions and the budget analysis) will be stored in a database. This minimizes writing and reading from the database.

User Changing Categories

The user might selectively override particular transactions to assign them to a different category. In this case, we would update the datastore for the categorized transactions. It would also signal a quick recomputation of the budget to decrement the item from the old category and increment the item in the other category.

We could also just recompute the budget from scratch. The budget analyzer is fairly quick as it just needs to look over the past few weeks of transactions for a single user.

Follow Up Questions

- How would this change if you also needed to support a mobile app?
- How would you design the component which assigns items to each category?
- How would you design the recommended budgets feature?
- How would you change this if the user could develop rules to categorize all transactions from a particular seller differently than the default?

9.8 Pastebin: Design a system like Pastebin, where a user can enter a piece of text and get a randomly generated URL for public access.

pg 145

SOLUTION

We can start with clarifying the specifics of this system.

Step 1: Scope the Problem

- The system does not support user accounts or editing documents.
- The system tracks analytics of how many times each page is accessed.
- Old documents get deleted after not being accessed for a sufficiently long period of time.
- While there isn't true authentication on accessing documents, users should not be able to "guess" docu-

ment URLs easily.

- The system has a frontend as well as an API.
- The analytics for each URL can be accessed through a “stats” link on each page. It is not shown by default, though.

Step 2: Make Reasonable Assumptions

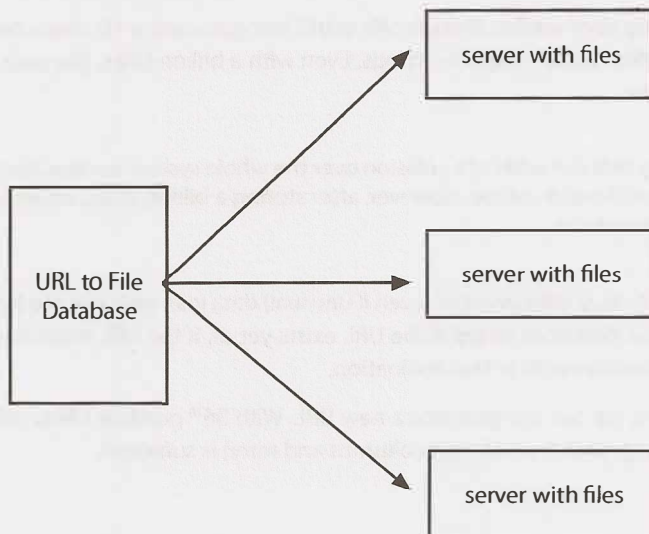
- The system gets heavy traffic and contains many millions of documents.
- Traffic is not equally distributed across documents. Some documents get much more access than others.

Step 3: Draw the Major Components

We can sketch out a simple design. We’ll need to keep track of URLs and the files associated with them, as well as analytics for how often the files have been accessed.

How should we store the documents? We have two options: we can store them in a database or we can store them on a file. Since the documents can be large and it’s unlikely we need searching capabilities, storing them on a file is probably the better choice.

A simple design like this might work well:



Here, we have a simple database that looks up the location (server and path) of each file. When we have a request for a URL, we look up the location of the URL within the datastore and then access the file.

Additionally, we will need a database that tracks analytics. We can do this with a simple datastore that adds each visit (including timestamp, IP address, and location) as a row in a database. When we need to access the stats of each visit, we pull the relevant data in from this database.

Step 4: Identify the Key Issues

The first issue that comes to mind is that some documents will be accessed much more frequently than others. Reading data from the filesystem is relatively slow compared with reading from data in memory. Therefore, we probably want to use a cache to store the most recently accessed documents. This will ensure

that items accessed very frequently (or very recently) will be quickly accessible. Since documents cannot be edited, we will not need to worry about invalidating this cache.

We should also potentially consider sharding the database. We can shard it using some mapping from the URL (for example, the URL's hash code modulo some integer), which will allow us to quickly locate the database which contains this file.

In fact, we could even take this a step further. We could skip the database entirely and just let a hash of the URL indicate which server contains the document. The URL itself could reflect the location of the document. One potential issue from this is that if we need to add servers, it could be difficult to redistribute the documents.

Generating URLs

We have not yet discussed how to actually generate the URLs. We probably do not want a monotonically increasing integer value, as this would be easy for a user to “guess.” We want URLs to be difficult to access without being provided the link.

One simple path is to generate a random GUID (e.g., 5d50e8ac-57cb-4a0d-8661-bcdee2548979). This is a 128-bit value that, while not strictly guaranteed to be unique, has low enough odds of a collision that we can treat it as unique. The drawback of this plan is that such a URL is not very “pretty” to the user. We could hash it to a smaller value, but then that increases the odds of collision.

We could do something very similar, though. We could just generate a 10-character sequence of letters and numbers, which gives us 36^{10} possible strings. Even with a billion URLs, the odds of a collision on any specific URL are very low.

This is not to say that the odds of a collision over the whole system are low. They are not. Any one specific URL is unlikely to collide. However, after storing a billion URLs, we are very likely to have a collision at some point.

Assuming that we aren't okay with periodic (even if unusual) data loss, we'll need to handle these collisions. We can either check the datastore to see if the URL exists yet or, if the URL maps to a specific server, just detect whether a file already exists at the destination.

When a collision occurs, we can just generate a new URL. With 36^{10} possible URLs, collisions would be rare enough that the lazy approach here (detect collisions and retry) is sufficient.

Analytics

The final component to discuss is the analytics piece. We probably want to display the number of visits, and possibly break this down by location or time.

We have two options here:

- Store the raw data from each visit.
- Store just the data we know we'll use (number of visits, etc.).

You can discuss this with your interviewer, but it probably makes sense to store the raw data. We never know what features we'll add to the analytics down the road. The raw data allows us flexibility.

This does not mean that the raw data needs to be easily searchable or even accessible. We can just store a log of each visit in a file, and back this up to other servers.

One issue here is that this amount of data could be substantial. We could potentially reduce the space usage considerably by storing data only probabilistically. Each URL would have a `storage_probability` associated with it. As the popularity of a site goes up, the `storage_probability` goes down. For example, a popular document might have data logged only one out of every ten times, at random. When we look up the number of visits for the site, we'll need to adjust the value based on the probability (for example, by multiplying it by 10). This will of course lead to a small inaccuracy, but that may be acceptable.

The log files are not designed to be used frequently. We will want to also store this precomputed data in a datastore. If the analytics just displays the number of visits plus a graph over time, this could be kept in a separate database.

URL	Month and Year	Visits
12ab31b92p	December 2013	242119
12ab31b92p	January 2014	429918
...

Every time a URL is visited, we can increment the appropriate row and column. This datastore can also be sharded by the URL.

As the stats are not listed on the regular pages and would generally be of less interest, it should not face as heavy of a load. We could still cache the generated HTML on the frontend servers, so that we don't continuously reaccess the data for the most popular URLs.

Follow-Up Questions

- How would you support user accounts?
- How would you add a new piece of analytics (e.g., referral source) to the stats page?
- How would your design change if the stats were shown with each document?

10

Solutions to Sorting and Searching

10.1 Sorted Merge: You are given two sorted arrays, A and B, where A has a large enough buffer at the end to hold B. Write a method to merge B into A in sorted order.

pg 149

SOLUTION

Since we know that A has enough buffer at the end, we won't need to allocate additional space. Our logic should involve simply comparing elements of A and B and inserting them in order, until we've exhausted all elements in A and in B.

The only issue with this is that if we insert an element into the front of A, then we'll have to shift the existing elements backwards to make room for it. It's better to insert elements into the back of the array, where there's empty space.

The code below does just that. It works from the back of A and B, moving the largest elements to the back of A.

```
1 void merge(int[] a, int[] b, int lastA, int lastB) {
2     int indexA = lastA - 1; /* Index of last element in array a */
3     int indexB = lastB - 1; /* Index of last element in array b */
4     int indexMerged = lastB + lastA - 1; /* end of merged array */
5
6     /* Merge a and b, starting from the last element in each */
7     while (indexB >= 0) {
8         /* end of a is > than end of b */
9         if (indexA >= 0 && a[indexA] > b[indexB]) {
10             a[indexMerged] = a[indexA]; // copy element
11             indexA--;
12         } else {
13             a[indexMerged] = b[indexB]; // copy element
14             indexB--;
15         }
16         indexMerged--; // move indices
17     }
18 }
```

Note that you don't need to copy the contents of A after running out of elements in B. They are already in place.

10.2 Group Anagrams: Write a method to sort an array of strings so that all the anagrams are next to each other.

pg 150

SOLUTION

This problem asks us to group the strings in an array such that the anagrams appear next to each other. Note that no specific ordering of the words is required, other than this.

We need a quick and easy way of determining if two strings are anagrams of each other. What defines if two words are anagrams of each other? Well, anagrams are words that have the same characters but in different orders. It follows then that if we can put the characters in the same order, we can easily check if the new words are identical.

One way to do this is to just apply any standard sorting algorithm, like merge sort or quick sort, and modify the comparator. This comparator will be used to indicate that two strings which are anagrams of each other are equivalent.

What's the easiest way of checking if two words are anagrams? We could count the occurrences of the distinct characters in each string and return `true` if they match. Or, we could just sort the string. After all, two words which are anagrams will look the same once they're sorted.

The code below implements the comparator.

```
1 class AnagramComparator implements Comparator<String> {
2     public String sortChars(String s) {
3         char[] content = s.toCharArray();
4         Arrays.sort(content);
5         return new String(content);
6     }
7
8     public int compare(String s1, String s2) {
9         return sortChars(s1).compareTo(sortChars(s2));
10    }
11 }
```

Now, just sort the arrays using this `compareTo` method instead of the usual one.

```
12 Arrays.sort(array, new AnagramComparator());
```

This algorithm will take $O(n \log(n))$ time.

This may be the best we can do for a general sorting algorithm, but we don't actually need to fully sort the array. We only need to *group* the strings in the array by anagram.

We can do this by using a hash table which maps from the sorted version of a word to a list of its anagrams. So, for example, `acre` will map to the list `{acre, race, care}`. Once we've grouped all the words into these lists by anagram, we can then put them back into the array.

The code below implements this algorithm.

```
1 void sort(String[] array) {
2     HashMapList<String, String> mapList = new HashMapList<String, String>();
3
4     /* Group words by anagram */
5     for (String s : array) {
6         String key = sortChars(s);
7         mapList.put(key, s);
8     }
```



```
9
10 / *Convert hash table to array */
11 int index = 0;
12 for (String key : mapList.keySet()) {
13     ArrayList<String> list = mapList.get(key);
14     for (String t : list) {
15         array[index] = t;
16         index++;
17     }
18 }
19 }
20
21 String sortChars(String s) {
22     char[] content = s.toCharArray();
23     Arrays.sort(content);
24     return new String(content);
25 }
26
27 / *HashMapList<String, Integer> is a HashMap that maps from Strings to
28 * ArrayList<Integer>. See appendix for implementation. */
```

You may notice that the algorithm above is a modification of bucket sort.

10.3 Search in Rotated Array: Given a sorted array of n integers that has been rotated an unknown number of times, write code to find an element in the array. You may assume that the array was originally sorted in increasing order.

EXAMPLE

Input: find 5 in {15, 16, 19, 20, 25, 1, 3, 4, 5, 7, 10, 14}

Output: 8 (the index of 5 in the array)

pg 150

SOLUTION

If this problem smells like binary search to you, you're right!

In classic binary search, we compare x with the midpoint to figure out if x belongs on the left or the right side. The complication here is that the array is rotated and may have an inflection point. Consider, for example, the following two arrays:

Array1: {10, 15, 20, 0, 5}

Array2: {50, 5, 20, 30, 40}

Note that both arrays have a midpoint of 20, but 5 appears on the left side of one and on the right side of the other. Therefore, comparing x with the midpoint is insufficient.

However, if we look a bit deeper, we can see that one half of the array must be ordered normally (in increasing order). We can therefore look at the normally ordered half to determine whether we should search the left or right half.

For example, if we are searching for 5 in Array1, we can look at the left element (10) and middle element (20). Since $10 < 20$, the left half must be ordered normally. And, since 5 is not between those, we know that we must search the right half.

In Array2, we can see that since $50 > 20$, the right half must be ordered normally. We turn to the middle (20) and right (40) element to check if 5 would fall between them. The value 5 would not; therefore, we search the left half.

The tricky condition is if the left and the middle are identical, as in the example array {2, 2, 2, 3, 4, 2}. In this case, we can check if the rightmost element is different. If it is, we can search just the right side. Otherwise, we have no choice but to search both halves.

```

1  int search(int a[], int left, int right, int x) {
2      int mid = (left + right) / 2;
3      if (x == a[mid]) { // Found element
4          return mid;
5      }
6      if (right < left) {
7          return -1;
8      }
9
10     /* Either the left or right half must be normally ordered. Find out which side
11      * is normally ordered, and then use the normally ordered half to figure out
12      * which side to search to find x. */
13     if (a[left] < a[mid]) { // Left is normally ordered.
14         if (x >= a[left] && x < a[mid]) {
15             return search(a, left, mid - 1, x); // Search left
16         } else {
17             return search(a, mid + 1, right, x); // Search right
18         }
19     } else if (a[mid] < a[right]) { // Right is normally ordered.
20         if (x > a[mid] && x <= a[right]) {
21             return search(a, mid + 1, right, x); // Search right
22         } else {
23             return search(a, left, mid - 1, x); // Search left
24         }
25     } else if (a[left] == a[mid]) { // Left or right half is all repeats
26         if (a[mid] != a[right]) { // If right is different, search it
27             return search(a, mid + 1, right, x); // search right
28         } else { // Else, we have to search both halves
29             int result = search(a, left, mid - 1, x); // Search left
30             if (result == -1) {
31                 return search(a, mid + 1, right, x); // Search right
32             } else {
33                 return result;
34             }
35         }
36     }
37     return -1;
38 }

```

This code will run in $O(\log n)$ if all the elements are unique. However, with many duplicates, the algorithm is actually $O(n)$. This is because with many duplicates, we will often have to search both the left and right sides of the array (or subarrays).

Note that while this problem is not conceptually very complex, it is actually very difficult to implement flawlessly. Don't feel bad if you had trouble implementing it without a few bugs. Because of the ease of making off-by-one and other minor errors, you should make sure to test your code very thoroughly.