### **IMDB** Data Management

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#### 1. OVERVIEW

The purpose of this paper is to serve as a final discussion of what we've done on our database project. It encompasses our ER model, the conversion to relationships, normalization of those relationships, constructing our database, cleaning the data for the database, and the implementation and usage of our program. The main focus of this paper will be on the work which has been done between the last paper and this paper, as well as any last minute design and implementation changes we have made due to time constraints.

#### 2. DATASET DESCRIPTION

The chosen IMDB dataset describes various aspects related to movies. Some of the examples of the data in the dataset is the data related to titles, actors, crews, episodes and ratings. All the data in the dataset is interrelated to different entities.

Below is a sample data representation. The data for actors can be represented by the following fields (nconst, primary-Name, birthYear, deathYear, primaryProfession, knownFor-Titles) and a sample data is (nm0000001, Fred Astaire, 1899 ,1987, soundtrack, actor, miscellaneous, tt0043044, tt0050419, tt0053137, tt0072308). So, given this information Fred Astaire is the primary name of the person whose primaryProfession is soundtrack, actor, and miscellaneous. The fields for sample data for movie title can be represented as (titleId, ordering, title, region, language, types, attributes, isOriginalTitle). An example of this is (tt0000001, 1, Carmencita spanyol tánc, HU, ", imdbDisplay, ", 0). In this case, we know that this movie, Carmencita - spanyol tánc, was released in Hungarian and is the original title. The attributes for the data related to episodes is as follows (tconst, parentTconst, seasonNumber, episodeNumber) and some sample data can be given by (tt0041951, tt0041038, 1, 9). This table is effectively a go between which helps maps an episode and its season to its entry in the title database. The dataset also contains the data regarding the movie crew, specifically the director and writer information for all the titles in IMDb where these fields are described (tconst, directors, writers). Sample data related to this can be represented as (tt0000001, nm0005690, "). This data is directly related to the principles as the tconst maps to values in the principles data. The data related to principles is given by (tconst, ordering, nconst, category, job, characters) and a sample data looks like (tt0000001, 1, nm1588970, self, ", ["Herself"]). The ratings for each movies is stored with the following attributes

(tconst, averageRating, numVotes), where a single rating looks like (tt0000001, 5.6, 1533).

Some of the user scenarios for our systems could be querying for the movies titles based on the laguange of the movie. For example, if the user wants to find all the movies in English language, the query would look something like:

(Select \* from title where language = 'en').

This would return a list of all the movies in our database with English language. In another scenario if the user wants to get a list of all famous movies casting his favourite actor, the user can also get the list of movies based on the actor. The query would looks something like.

(Select knownForTitles from actors where name = 'Brad Pitt').

These are some of the high level scenarios, we can further narrow them based on the filters selected by the user.

#### 3. DATABASE AND RELATIONAL MODEL

#### 3.1 ER-Model and database structure

All the tables and the constraints are described as follows: users (uid,passwd,age,language) PK(uid).

history (uid,tconst,date) PK(uid,tconst)  $FK_1$  (uid)  $FK_2$  (tconst). rating (uid,tconst,rating,isVote) PK(uid,tconst)  $FK_1$  (uid)  $FK_2$  (tconst).

general\_movie (tconst,title,isAdult,type)PK(tconst). genres (tconst,genre)PK(tconst,genre) FK(tconst).

localize (tconst,local-name,language,isOriginal) PK(tconst,local-name,language) FK(tconst).

 $tvSeries(series-tconst,isOver)\ PK(series-tconst)\ FK(series-tconst).\\ tvEpisode(episode-tconst,episode-number)\ PK(episode-tconst)\\ FK(episode-tconst).$ 

 $\label{eq:has} has (series-tconst, episode-tconst, season-number, broadcast-year) PK (series-tconst, episode-tconst). FK (series-tconst, episode-tconst)$ 

$$\label{eq:movie-tconst} \begin{split} & movie(movie-tconst, release-year, runtime) \ PK(movie-tconst) \\ & FK(movie-tconst). \end{split}$$

videoGame(game-tconst,sells-year) PK(game-tconst) FK(game-tconst).

news(news-tconst) PK(news-tconst) FK(news-tconst). persons(primary-name,birth-year,death-year) PK (primary-name, birth-year).

professions (primary-name,birth-year,profession) PK (primary-name, birth-year, profession) FK (primary-name, birth-year). acts (act-name, birth-year, movie-tconst, character) PK (act-name, birth-year, movie-tconst, character)  $FK_1$  (act-name,

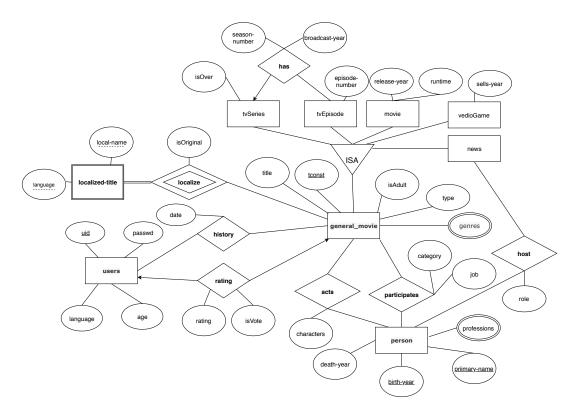


Figure 1: ER Model for our Application

birth-year)  $FK_2$  (movie-tconst). participates(act-name, birth-year, movie-tconst, category, job) PK (act-name, birth-year, movie-tconst)  $FK_1$  (act-name, birth-year)  $FK_2$ (movie-tconst).

host(news-tconst, host-name, birth-year, role) PK(news-tconst, host-name, birth-year)  $FK_1$  (news-tconst)  $FK_2$  (host-name, birth-year)

#### 3.2 Raw data importing

In order to manipulate the IMDB data, we need to import the raw data from a .tsv file into our database. For this part, I choose to create tables in the same way that IMDB did. We create and maintain 'title\_akas', 'title\_basics', 'title\_principals', 'title\_crews', 'title\_episodes', 'title\_ratings' and 'name\_basics' tables. We'll keep all the data along with every attribute even though there some of those attributes may have null values. Because we've kept all the data, we can manipulate these table and preform each query the way we want via SQL.

#### 3.3 Raw data cleaning

Our data cleaning has two parts. The first step is to remove noisy data which has null values in a significant attribute column like 'birth-year' in 'persons'. The second step is to delete duplicated data.

What we got from IMDB is all raw data therefore we can not rely on its integrity and thus we must clean it. For instance, in the 'persons' table, our primary key is primary name and birth year. However, in the raw data, we may find some entries which do not have a birth year value. We will definitely remove this kind of data. At the same time,

we assume that primary name and birth year can uniquely identify one person. So, when we have several tuples with same primary-title and birth-year, our solution is to record one of them in our database.

The way I do it is pretty straightforward. After we import all the raw data, we select the real data and generate a bright table with valid data. The data cleaning SQL script contains the query which will do the cleaning and where we store the data that is valid. Below is an example of a basic query which would remove all null values from the data.

SELECT primary-name, birth-year, death-year

FROM raw\_names WHERE birth-year IS NOT NULL;

Since we have some composite keys as primary keys in our databases, we have to clean all the duplicated data which has the same primary key attributes. For example, in the 'persons' table, we want birthYear and primary-name to be the primary key. We have to remove the data for which these two attributes have the same value. The following query shows how I removed the duplicate data.

CREATE TABLE new\_data

SELECT \* FROM 'name\_basics' N1

GROUP BY (N1.primary-name, N1.birthYear);

What's more, we clean the data in participates and acts tables that have person who is not in our persons data. Here show the way we clean those bad data and get the data of acts table.

select distinct \*

from 'title\_principals' old

where old.category = 'actor'

and old.characters is not null

or old.category = 'actress' AND old.characters is not null and exists ( select \*

```
from surrogate_person s
where s.nconst = old.nconst)
and exists ( select *
from general_movies g
where g.tconst = old.tconst);
```

Now, all we need to do is drop the old raw data and use the cleaned data to generate our database and implement our application's functions. We can also find that after data cleaning, the size of our database decreased significantly.

#### 3.4 Table Construction

We have solved some problems when we construct tables. First, the performance of our system is not ideal when it comes to huge size data set like participates table. We decided to generate more sub-tables based on the type of participation like producer, writer and director. These tables keep the person id, movie id and his/her job in it.

Second, the original data has attributes with arrays, all we need to split this attribute and generate a new data table. When it comes to the professions attribute of person. The original data looks like 'actor,producer,soundtrack'. I use the 'help\_topic' in mysql and here is the script I write to split these attribute and construct new table.

```
create table professions as select a.'primary_name', a.'birth_year', substring_index (substring_index(a.profession,',',b.'help_topic_id'+1),',',-1) from 'old_professions' a join mysql.'help_topic' b on b.'help_topic_id' < (length(a.profession) - length(replace(a.profession,',',"))+1) order by a.'primary_name',a.'birth_year';
```

Now we are finally able to use the database to implement system functions.

#### 4. DESIGN CHOICES

#### 4.1 Application Design

Our original plan for application design was a simple Java server which would handle HTTP requests which would come from a web browser and using HTML and JavaScript to display the results returned. We've maintained this approach but have decided to move away from using Java as our web server to using Python with Flask as it simplifies the process. We no longer have to deal with handling individual requests, instead we can focus on making the queries and presenting the data back to the user. So really all this switch does is change the language we are working in while also providing us a framework which simplifies the process of managing a web server. We will still have to write individual queries, we will still have to write user interfaces to get data from the user, and we will still have to present the data to the user in an easy to read format. An additional reason we have switched away from Java while writing the back end is because there exists integration's between Python and R that will help make the later data mining component easier.

#### 4.2 Query Interface Design

Our first step in designing out query interface was figuring out what queries we would support. We came up with a list of queries that seemed interesting and were complicated enough to warrant a queryable interface for them. We each generated a list of 5 queries we felt fulfilled these require-

ments. Then, as a team, we picked the most interesting among those and decided to work on them. We realized quite quickly that these queries would need to be on separate pages as it would simplify the input for the user, but it would also make our lives easier to as well. Rather than having to deal with multiple HTML forms on the same page, we would instead be working with a single form on a single page. We also decided it would make the most sense to take advantage of Flask's built in templating system. This allowed us to write one template which would use to display results for all of the queries.

The usage is actually rather straight forward. Our homepage has a list of English descriptions of queries and then a button that links to the page which requires you to enter the information you wish to query with. The user clicks "submit" and then they are automatically routed to a page which displays the results.

#### 4.3 Query statement

As we have given 5 query plus our 5 query supports, our system have 10 query support provided. In order to simplify the query statement and make it perform faster. Instead of join tables in select statement, we create view in advance in some of the scenarios. At the beginning, we create a view which join the persons table with its surrogate key.

```
create view personx as select sur.nconst, p.primary_name, p.birth_year, p.death_year from persons p, surrogate_person sur where p.birth_year = sur.birth_year and p.primary_name = sur.primary_name;
```

1. List the names of alive actors whose name starts with a given keyword (such as "Phi") and did not participate in any movie in a given year (such as 2014).

I create the view which join our participates table with movie table.

```
create view movie_participate as
select mov.movie_tconst, par.nconst, mov.release_year
from movie mov, participates par
where mov.'movie_tconst' = par.tconst;
Now, I have to select the alive person with given name and
```

Now, I have to select the alive person with given name and he/she has to be a actor/actress but do not participates in any movie in 2014.

```
any movie in 2014.

select per.'primary_name'
from personx per
where per.'death_year' IS NULL
and per.'primary_name' LIKE 'Phi%'
and not exists(
select *
from movie_participate par
where par.nconst = per.nconst
and par.'release_year' = 2014)
and exists( select *
from acts a
where a.nconst = per.nconst);
```

2.List the names of alive producers who have produced more than a given number (such as 50) of talk shows in a given year (such as 2017) and whose name contains a given keyword (such as "Gill").

```
SELECT per.'primary_name' as name
FROM personx per
WHERE per.'primary_name' LIKE '%e%'
AND per.'death_year' IS NULL
```

```
AND per.nconst IN (
                                                                  and gen.runtime = 90
  SELECT pro.nconst
                                                                  and exists (
  FROM producers pro, talkshow tak
                                                                  select *
  WHERE pro.tconst = tak.tconst
                                                                  from previous_rating previous
  AND tak. 'show_year' = 2014
                                                                  where h.series_tconst = previous.tconst and rating > 4)
  group by pro.nconst
                                                                  group by h.series_tconst, gen.title
  having count(*) > 1);
                                                                  having count(*) > 5;
3.List the average runtime for movies whose original title
                                                                7. List all the movies with actor (actor name) and which are
contain a given keyword such as ("star") and were written
                                                                in language (English, Spanish etc).
                                                                  Select distinct lo.local_name, per.primary_name, lo.lang
by somebody who is still alive.
  SELECT AVG(gen.runtime)
                                                                  from general_movies m, personx per, localize lo, acts act
  FROM 'general_movies' gen
                                                                  where act.nconst = per.nconst
  WHERE title LIKE '%star%'
                                                                  and lo.tconst = m.tconst
  AND gen.type = 'movie'
                                                                  and m.tconst = act.tconst
  AND gen.tconst IN (
                                                                  and m.type = 'movie' and lo.lang = 'en'
  SELECT tconst
                                                                  and per.primary_name like '%a%';
  FROM writers w
                                                                8.List all the producers who died before their movie was
  WHERE exists (
  SELECT nconst
                                                                  select distinct per.primary_name
  FROM personx per
                                                                  from producers pro, personx per
  WHERE per.'death_year' IS NULL
                                                                  where pro.nconst = per.nconst
  AND per.nconst = w.nconst));
                                                                  and exists (select *
4. List the names of alive producers with the greatest number
                                                                  from movie mov
                                                                  where pro.tconst = mov.movie\_tconst
of long-run movies produced (runtime greater than 120 min).
  create view producer_movie_person as
                                                                  and mov.release_year > per.death_year);
  select pro.nconst, pro.tconst, gen.title,
                                                                9.List all the movies where the actor and director both had
  gen.type, gen.runtime, per.primary_name,
                                                                the same birth year contributed to the same movie.
                                                                I will create 2 views act_name_birth and director_name_birth
  per.birth\_year,\ per.death\_year
  from producers pro, general_movies gen, personx per
                                                                to keep all the birth year of actors and directors. Then I
  where pro.tconst = gen.tconst and pro.nconst = per.nconst;
                                                                join these 2 tables to get the pairs of actor and director who
                                                                contribute to the same movie. Now I get view dir_act_mov.
Now I can select producer's name
                                                                  create view act_name_birth as
  select primary_name, max(runtime)
  from producer_movie_person
                                                                  select p.primary_name, p.nconst, p.birth_year, act.tconst
  where runtime > 120 and death_year is null
                                                                  from acts act, personx p
  group by nconst, primary_name;
                                                                  where p.nconst = act.nconst;
5.List the unique name pairs of actors who have acted to-
                                                                  create view director_name_birth as
gether in more than a given number (such as 2) movies and
                                                                  select p.primary_name, p.nconst, p.birth_year, dir.tconst
sort them by average movie rating (of those they acted to-
                                                                  from directors dir, personx p
                                                                  where p.nconst = dir.nconst;
gether).
  create view tmp_act as
                                                                  create view dir_act_mov as
  select a.nconst, a.tconst, p.primary_name
                                                                  select dir.birth_year as dir_birth, dir.nconst as dir_nconst,
  from acts a, personx p
                                                                act.birth_year as act_birth,
                                                                  act.nconst as act_nconst, dir.tconst
  where a.nconst = p.nconst
                                                                  from director_name_birth dir, act_name_birth act
  create view act_act as
  select act1.primary_name as a1,
                                                                  where dir.tconst = act.tconst;
                                                                Now I select the titles which are under given requirements.
  act2.primary_name as a2, act1.tconst
  from tmp_act act1, tmp_act act2
                                                                select distinct gen.title
  where act1.tconst = act2.tconst
                                                                  from dir_act_mov a, general_movies gen
  and cast(substring(act1.nconst,3) as signed)
                                                                  where a.dir_birth = a.act_birth
  > cast(substring(act2.nconst,3) as signed);
                                                                  and gen.tconst = a.tconst
Now I select the pairs with descending rating.
                                                                  and not a.dir_nconst = a.act_nconst;
  select distinct a.a1, a.a2, p.rating
                                                                10. List all the shows which have a total run time less than
  from act_act a, previous_rating p
                                                                a particular value.
  where p.tconst = a.tconst
                                                                  select mov.title
  group by a.a1, a.a2, p.rating
                                                                  from general_movies mov , generes gen
  having count(*) > 2
                                                                  where mov.tconst = gen.tconst
                                                                  and gen.genre like '%show%'
  order by p.rating desc;
6.List the tv series with x number of episodes and which has
                                                                  and mov.runtime < 10
a rating above 4 for the last 5 years.
  select h.series_tconst, gen.title
  from has h, tvepisode epi, general_movies gen
                                                                5. APPLICATION DEMO
  where h.episode_tconst = epi.episode_tconst
```

and  $gen.tconst = h.series\_tconst$ 

The first thing which you get dropped into is the homepage. As you can see in the figure 2 you are given the list supported queries which you can access by clicking the button.

When clicking the first query button, you're presented with two text fields, as shown in figure 3. These are the parameters of the query, so in this case, the results returned will contain the list of actors whose names start with the keyword "Phi" and didn't participate in a movie for the year 2014.

Figure 4 shows the results of the query shown in figure 3. You can quickly navigate home by clicking the home button. From here on out, we will just show the search parameter page and then the results from the query.

#### 5.1 Remaining Screenshots

#### 6. WORK LOAD DISTRIBUTION

The workload was not entirely uniform but everyone did their best to contribute at each step of the process. The initial design of the database was handled primarily by Yifei and Zhou. They worked together to create our ER models. From there, Yifei and Richard worked together to handle normalization, essentially they analyzed the ER model, translated that model into a relationship model, and then verified that we were in BCNF. All while this was going on Ajeeta and Zhou worked on the first paper. Ajeeta worked to make the template which was used to display all of our results. We all worked together to write the queries since as we all went back and forth and help each other when one of us got stuck.

#### **IMDB Database**

The list of query support provided by our system. Please click on check and try out the query

1. List the names of alive actors whose name starts with a given keyword (such as "Phi") and did not participate in any movie in a given year (such as 2014). Check

2. List the names of alive producers who have produced more than a given number (such as 50) of talk shows in a given year (such as 2017) and whose name contains a given keyword (such as "Gill"). Check

3. List the average runtime for movies whose original title contain a given keyword such as "star") and were written by somebody who is still alive. Check

4. List the names of alive producers with the greatest number of long-run movies produced (runtime greater than 120 min). Check

5. List the unique name pairs of actors who have acted together in more than a given number (such as 2) movies and sort them by average movie rating (of those they acted together). Check

6. List the tv series with x (example 7) number of episodes and which has a rating above x (example 4) with minimum runtime of (example 90). Check

7. List all the movies with actor (actor name ) and which are in language (English, Spanish etc). Check

8. List all the actors and producers who died before their movie was released. Check

9. List all the movies where the actor and director both had the same birth year contributed to the same movie. Check

10. List all the users who gave rating over 8 (or any rating value) for the last x(number ) of years. Check

11. List all the shows which have a total run time less than a particular value Check

Figure 2: Home page of the website

Home

Name starts with Phi

Year 2014

Figure 3: Query 1 Search parameter input

Actor Name	
Phi Nguyen	
Phi Nhung	
Phil Abrams	
Phil Adams	_
Phil Addis	
Phil Agland	
Phil Allora	
Phil Amato	
Phil Angelides	_
Phil Armijo	
Phil Arthur	
Phil Baker	
Phil Balsley	
Phil Barney	
Phil Baron	
Phil Baroni	
Phil Blevins	
Phil Bloom	
Phil Bonifield	
Phil Boot	_
Phil Boroff	
Phil Bourassa	
Phil Bradley	
Phil Bredesen	
Phil Brock	
Phil Bronstein	
Phil Brookes	
Phil Brough	
Phil Buckman	_

Figure 4: Query 1 Results

		-
Н	lom	е

2. List the names of alive producers who have produced more than a given number (such as 50) of talk shows in a given year (such as 2017) and whose name contains a given keyword (such as "Gill").

Number 1	
Year 2014	
Name Contains e	
submit	

Figure 5: Query 2 search parameter input

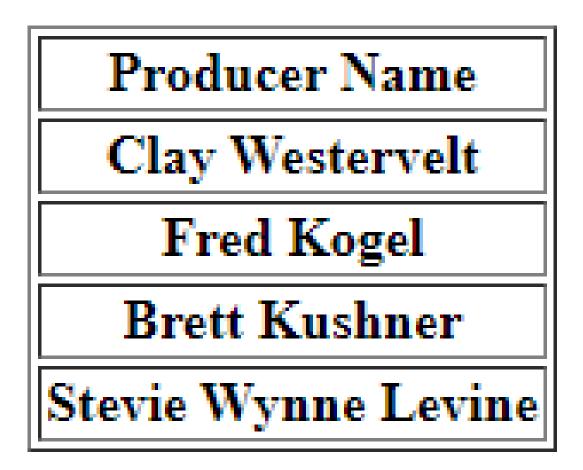


Figure 6: Query 2 results

Home

3. List the average runtime for movies whose original title contain a given keyword such as ("star") and were written by somebody who is still alive.

Contains Keyword the

Figure 7: Query 3 search parameter input



Figure 8: Query 3 results

Home

4. List the names of alive producers with the greatest number of long-run movies produced (runtime greater than 120 min).

Figure 9: Query 4 search parameter input

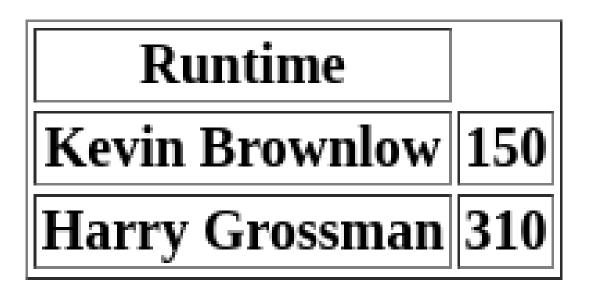


Figure 10: Query 4 results

Home

5. List the unique name pairs of actors who have acted together in more than a given number (such as 2) movies and sort them by average movie rating (of those they acted together).

Number of movies 2

submit

Figure 11: Query 5 search parameter input

Actor Name 1	Actor Name 2	Rating
Jerry Seinfeld	Julia Louis-Dreyfus	9.6
David Duchovny	Gillian Anderson	9.2
Woody Harrelson	Matthew McConaughey	9.2
Terry Farrell	Michael Dorn	9.1
Jerry Seinfeld	Julia Louis-Dreyfus	9.1
David Duchovny	Gillian Anderson	9.1
Jonathan Frakes	Michael Dorn	9.0
Lacey Chabert	Neve Campbell	9.0
Jerry Seinfeld	Julia Louis-Dreyfus	9.0
Edward Asner	Hank Azaria	9.0
David Duchovny	Gillian Anderson	9.0
Kirsten Dunst	Ewan McGregor	9.0
Billy Bob Thornton	Ewan McGregor	9.0
Rose McGowan	Alyssa Milano	8.9
Jerry Seinfeld	Julia Louis-Dreyfus	8.9
Terry Farrell	Michael Dorn	8.9
Jonathan Frakes	Michael Dorn	8.9
David Duchovny	Gillian Anderson	8.9
Lili Taylor	Timothy Hutton	8.9
Jerry Seinfeld	Julia Louis-Dreyfus	8.8
Ron Perlman	Linda Hamilton	8.8
Rose McGowan	Alyssa Milano	8.8
Lacey Chabert	Neve Campbell	8.8
Robert Duncan McNeill	Robert Beltran	8.8
Kate Mulgrew	Robert Beltran	8.8
Kate Mulgrew	Robert Duncan McNeill	8.8
David Duchovny	Gillian Anderson	8.8
Michael Madsen	Harvey Keitel	8.8
Tim Roth	Harvey Keitel	8.8
Tim Roth	Michael Madsen	8.8
Robin Wright	Kevin Spacey	8.8
Diane Lane	Tommy Lee Jones	8.7
Robert Duvall	Tommy Lee Jones	8.7
Robert Duvall	Diane Lane	8.7
Danny Glover	Tommy Lee Jones	8.7
Danny Glover	Diane Lane	8.7
Danny Glover	Robert Duvall	8.7
Rose McGowan	Alyssa Milano	8.7
Lacey Chabert	Neve Campbell	8.7
Jerry Seinfeld	Julia Louis-Dreyfus	8.7
Jonathan Frakes	Michael Dorn	8.7
David Duchovny	Gillian Anderson	8.7
James Arness	Bruce Boxleitner	8.7
Stephen Fry	Rowan Atkinson	8.6
Jonathan Frakes	Michael Dorn	8.6
Gates McFadden	Michael Dorn	8.6
Gates McFadden	Jonathan Frakes	8.6
Marina Sirtis	Michael Dorn	8.6
Marina Sirtis	Jonathan Frakes	8.6
Brent Spiner	Michael Dorn	8.6
Brent Spiner	Jonathan Frakes	8.6
Brent Spiner	Gates McFadden	8.6
Brent Spiner	Marina Sirtis	8.6
Wil Wheaton	Michael Dorn	8.6
		_
Wil Wheaton	Jonathan Frakes	8.6
Wil Wheaton Wil Wheaton	Jonathan Frakes Gates McFadden	8.6 8.6
Wil Wheaton Wil Wheaton Wil Wheaton	Jonathan Frakes Gates McFadden Marina Sirtis	8.6 8.6 8.6
Wil Wheaton Wil Wheaton Wil Wheaton Wil Wheaton	Jonathan Frakes Gates McFadden Marina Sirtis Brent Spiner	8.6 8.6 8.6 8.6
Wil Wheaton Wil Wheaton Wil Wheaton Wil Wheaton Majel Barrett	Jonathan Frakes Gates McFadden Marina Sirtis Brent Spiner Michael Dorn	8.6 8.6 8.6 8.6 8.6
Wil Wheaton Wil Wheaton Wil Wheaton Wil Wheaton Wil Wheaton Majel Barrett Majel Barrett	Jonathan Frakes Gates McFadden Marina Sirtis Brent Spiner Michael Dorn Jonathan Frakes	8.6 8.6 8.6 8.6 8.6 8.6
Wil Wheaton Wil Wheaton Wil Wheaton Wil Wheaton Majel Barrett Majel Barrett Majel Barrett	Jonathan Frakes Gates McFadden Marina Sirtis Brent Spiner Michael Dorn Jonathan Frakes Gates McFadden	8.6 8.6 8.6 8.6 8.6 8.6
Wil Wheaton Wil Wheaton Wil Wheaton Wil Wheaton Majel Barrett Majel Barrett Majel Barrett Majel Barrett	Jonathan Frakes Gates McFadden Marina Sirtis Brent Spiner Michael Dorn Jonathan Frakes Gates McFadden Marina Sirtis	8.6 8.6 8.6 8.6 8.6 8.6 8.6
Wil Wheaton Wil Wheaton Wil Wheaton Wil Wheaton Majel Barrett Majel Barrett Majel Barrett Majel Barrett	Jonathan Frakes Gates McFadden Marina Sirtis Brent Spiner Michael Dorn Jonathan Frakes Gates McFadden	8.6 8.6 8.6 8.6 8.6 8.6 8.6 8.6
Wil Wheaton Wil Wheaton Wil Wheaton Wil Wheaton Majel Barrett Majel Barrett Majel Barrett Majel Barrett	Jonathan Frakes Gates McFadden Marina Sirtis Brent Spiner Michael Dorn Jonathan Frakes Gates McFadden Marina Sirtis	8.6 8.6 8.6 8.6 8.6 8.6 8.6
Wil Wheaton Wil Wheaton Wil Wheaton Wil Wheaton Majel Barrett Majel Barrett Majel Barrett Majel Barrett	Jonathan Frakes Gates McFadden Marina Sirtis Brent Spiner Michael Dorn Jonathan Frakes Gates McFadden Marina Sirtis Brent Spiner	8.6 8.6 8.6 8.6 8.6 8.6 8.6 8.6
Wil Wheaton Wil Wheaton Wil Wheaton Wil Wheaton Majel Barrett Majel Barrett Majel Barrett Majel Barrett Majel Barrett Majel Barrett	Jonathan Frakes Gates McFadden Marina Sirtis Brent Spiner Michael Dorn Jonathan Frakes Gates McFadden Marina Sirtis Brent Spiner Wil Wheaton	8.6 8.6 8.6 8.6 8.6 8.6 8.6 8.6 8.6
Wil Wheaton Wil Wheaton Wil Wheaton Wil Wheaton Majel Barrett Majel Barrett Majel Barrett Majel Barrett Majel Barrett Majel Barrett	Jonathan Frakes Gates McFadden Marina Sirtis Brent Spiner Michael Dorn Jonathan Frakes Gates McFadden Marina Sirtis Brent Spiner Wil Wheaton Gillian Anderson	8.6 8.6 8.6 8.6 8.6 8.6 8.6 8.6 8.6 8.6
Wil Wheaton Wil Wheaton Wil Wheaton Wil Wheaton Majel Barrett David Duchovny Robert Duncan McNeill	Jonathan Frakes Gates McFadden Marina Sirtis Brent Spiner Michael Dorn Jonathan Frakes Gates McFadden Marina Sirtis Brent Spiner Wil Wheaton Gillian Anderson Robert Beltran	8.6 8.6 8.6 8.6 8.6 8.6 8.6 8.6 8.6 8.6
Wil Wheaton Wil Wheaton Wil Wheaton Wil Wheaton Majel Barrett	Jonathan Frakes Gates McFadden Marina Sirtis Brent Spiner Michael Dorn Jonathan Frakes Gates McFadden Marina Sirtis Brent Spiner Wil Wheaton Gillian Anderson Robert Beltran	8.6 8.6 8.6 8.6 8.6 8.6 8.6 8.6 8.6 8.6
Wil Wheaton Wil Wheaton Wil Wheaton Wil Wheaton Majel Barrett David Duchovny Robert Duncan McNeill Kate Mulgrew Kate Mulgrew Ron Perlman	Jonathan Frakes Gates McFadden Marina Sirtis Brent Spiner Michael Dorn Jonathan Frakes Gates McFadden Marina Sirtis Brent Spiner Wil Wheaton Gillian Anderson Robert Beltran Robert Duncan McNeill Linda Hamilton	8.6 8.6 8.6 8.6 8.6 8.6 8.6 8.6 8.6 8.6
Wil Wheaton Wil Wheaton Wil Wheaton Wil Wheaton Majel Barrett En Majel Barrett David Duchovny Robert Duncan McNeill Kate Mulgrew Kate Mulgrew Ron Perlman Clancy Brown	Jonathan Frakes Gates McFadden Marina Sirtis Brent Spiner Michael Dorn Jonathan Frakes Gates McFadden Marina Sirtis Brent Spiner Wil Wheaton Gillian Anderson Robert Beltran Robert Duncan McNeill Linda Hamilton Adrienne Barbeau	8.6 8.6 8.6 8.6 8.6 8.6 8.6 8.6 8.6 8.6
Wil Wheaton Wil Wheaton Wil Wheaton Wil Wheaton Majel Barrett Chavid Duchovny Robert Duncan McNeill Kate Mulgrew Kate Mulgrew Ron Perlman Clancy Brown Rose McGowan	Jonathan Frakes Gates McFadden Marina Sirtis Brent Spiner Michael Dorn Jonathan Frakes Gates McFadden Marina Sirtis Brent Spiner Wil Wheaton Gillian Anderson Robert Beltran Robert Beltran Robert Duncan McNeill Linda Hamilton Adrienne Barbeau Alyssa Milano	8.6 8.6 8.6 8.6 8.6 8.6 8.6 8.6 8.6 8.6
Wil Wheaton Wil Wheaton Wil Wheaton Wil Wheaton Majel Barrett Charel Barrett David Duchovny Robert Duncan McNeill Kate Mulgrew Kate Mulgrew Kate Mulgrew Ron Perlman Clancy Brown Rose McGowan Ron Perlman	Jonathan Frakes Gates McFadden Marina Sirtis Brent Spiner Michael Dorn Jonathan Frakes Gates McFadden Marina Sirtis Brent Spiner Wil Wheaton Gillian Anderson Robert Beltran Robert Beltran Robert Duncan McNeill Linda Hamilton Adrienne Barbeau Alyssa Milano Mark Hamill	8.6 8.6 8.6 8.6 8.6 8.6 8.6 8.6
Wil Wheaton Wil Wheaton Wil Wheaton Wil Wheaton Majel Barrett Chavid Duchovny Robert Duncan McNeill Kate Mulgrew Kate Mulgrew Ron Perlman Clancy Brown Rose McGowan	Jonathan Frakes Gates McFadden Marina Sirtis Brent Spiner Michael Dorn Jonathan Frakes Gates McFadden Marina Sirtis Brent Spiner Wil Wheaton Gillian Anderson Robert Beltran Robert Beltran Robert Duncan McNeill Linda Hamilton Adrienne Barbeau Alyssa Milano	8.6 8.6 8.6 8.6 8.6 8.6 8.6 8.6 8.6 8.6

Figure 12: Query 5 results

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submit

6. List the tv series with x (example 7) number of	f episodes and which has a rating above x (example 4) with minimum runtime of (example 90)
Number of episodes 5	
Minimum Rating 4	
Running time 90	

Figure 13: Query 6 search parameter input

Home Title Your Show of Shows Producers' Showcase Ford Star Jubilee Playhouse 90 Bandstand The DuPont Show of the Month **Arrest and Trial Another World Cimarron Strip** The Joey Bishop Show The Name of the Game The David Frost Show The Dick Cavett Show The Pink Panther Show Longstreet Banacek **Hec Ramsey** Madigan Hawkins Movin' On Saturday Night Live Switch Bergerac SCTV Network 90 **Matt Houston** Die Schwarzwaldklinik Navarro Rivalen der Rennbahn

Figure 14: Query 6 results

One Foot in the Crave

7. List all the movies with actor (actor i	name ) and which are in language (English, S
Actor name starts with Baby	
Language en	

Figure 15: Query 7 search parameter input

Title	Name	Language
The Viking	Bob Bartlett	en
The Carson City Kid	Bob Steele	en
Road to Morocco	Bob Hope	en
Nazty Nuisance	Bobby Watson	en
Nazty Nuisance	Bobby Watson	en
They Got Me Covered	Bob Hope	en
Belle of the Yukon	Bob Burns	en
The Princess and the Pirate	Bob Hope	en
Bud Abbott and Lou Costello in Hollywood	Bob Haymes	en
Live Wires	Bobby Jordan	en
My Favorite Brunette	Bob Hope	en
Where There's Life	Bob Hope	en
Der Apfel ist ab	Bobby Todd	en
The Fallen Idol	Bobby Henrey	en
Hallo, Fräulein!	Bobby Todd	en
The Window	Bobby Driscoll	en
The Lemon Drop Kid	Bob Hope	en
Road to Bali	Bob Hope	en
Casanova's Big Night	Bob Hope	en
That Certain Feeling	Bob Hope	en
Beau James	Bob Hope	en
Gun Duel in Durango	Bobby Clark	en
China Doll	Bob Mathias	en
Alias Jesse James	Bob Hope	en
The Beatniks	Bob Wells	en
Bachelor in Paradise	Bob Hope	en
Hell Is for Heroes	Bobby Darin	en
Pressure Point	Bobby Darin	en
The Road to Hong Kong	Bob Hope	en
McHale's Navy	Bob Hastings	en
10.22	Pob Do Longo	

Figure 16: Query 7 results

Home

See the results

Figure 17: Query 8 search parameter "input"

Home
Producer Name
David Carradine
Sydney Pollack
Tony Scott Ed Vassallo
Claude Baks
Socrates Ballis
Humbert Balsan
Marc Beaudet
Christian Blackwood
Roger Blanc
David Bombyk
Jim Booth
Larry Brezner Rafi Bukai
Frank Capra Jr.
Béatrice Caufman
Mario Cecchi Gori
René Cleitman
Larry Darmour
Francisco del Villar Nancy Dickerson
Paolo Ferrara
Gil Friesen
Fernando de Fuentes hij
Fernando de Fuentes
Alejandro Galindo
Georges Glass
Frank Glicksman Leslie Grantham
Harold Greenberg
Jesús Grovas
Samuel Hadida
Kirk Edward Hansen
Olle Hellbom
S. Hillkowitz
Gregg Hoffman
Hans Hömberg
Thomas H Ince
Thomas H. Ince Peter Jamison
Peter Jamison
Peter Jamison Otto Kahn Mikheil Kalatozishvili
Peter Jamison Otto Kahn Mikheil Kalatozishvili Ferenc Kardos
Peter Jamison Otto Kahn Mikheil Kalatozishvili Ferenc Kardos István Kardos
Peter Jamison Otto Kahn Mikheil Kalatozishvili Ferenc Kardos István Kardos Kirin Kiki
Peter Jamison Otto Kahn Mikheil Kalatozishvili Ferenc Kardos István Kardos Kirin Kiki Julie Kirkham
Peter Jamison Otto Kahn Mikheil Kalatozishvili Ferenc Kardos István Kardos Kirin Kiki Julie Kirkham Werner Koenig
Peter Jamison Otto Kahn Mikheil Kalatozishvili Ferenc Kardos István Kardos Kirin Kiki Julie Kirkham
Peter Jamison Otto Kahn Mikheil Kalatozishvili Ferenc Kardos István Kardos Kirin Kiki Julie Kirkham Werner Koenig Öscar Kramer Gulshan Kumar
Peter Jamison Otto Kahn Mikheil Kalatozishvili Ferenc Kardos István Kardos Kirin Kiki Julie Kirkham Werner Koenig Öscar Kramer Gulshan Kumar Franklin R. Levy Amilcar Lyra
Peter Jamison Otto Kahn Mikheil Kalatozishvili Ferenc Kardos István Kardos Kirin Kiki Julie Kirkham Werner Koenig Öscar Kramer Gulshan Kumar Franklin R. Levy Amilcar Lyra A.V. Meiyappan
Peter Jamison Otto Kahn Mikheil Kalatozishvili Ferenc Kardos István Kardos Kirin Kiki Julie Kirkham Werner Koenig Öscar Kramer Gulshan Kumar Franklin R. Levy Amilcar Lyra A.V. Meiyappan Robert de Nesle
Peter Jamison Otto Kahn Mikheil Kalatozishvili Ferenc Kardos István Kardos Kirin Kiki Julie Kirkham Werner Koenig Öscar Kramer Gulshan Kumar Franklin R. Levy Amilcar Lyra A.V. Meiyappan Robert de Nesle Robert F. Newmyer
Peter Jamison Otto Kahn Mikheil Kalatozishvili Ferenc Kardos István Kardos Kirin Kiki Julie Kirkham Werner Koenig Öscar Kramer Gulshan Kumar Franklin R. Levy Amilcar Lyra A.V. Meiyappan Robert de Nesle Robert F. Newmyer Milan Nikolic
Peter Jamison Otto Kahn Mikheil Kalatozishvili Ferenc Kardos István Kardos Kirin Kiki Julie Kirkham Werner Koenig Öscar Kramer Gulshan Kumar Franklin R. Levy Amilcar Lyra A.V. Meiyappan Robert de Nesle Robert F. Newmyer
Peter Jamison Otto Kahn Mikheil Kalatozishvili Ferenc Kardos István Kardos Kirin Kiki Julie Kirkham Werner Koenig Öscar Kramer Gulshan Kumar Franklin R. Levy Amilcar Lyra A.V. Meiyappan Robert de Nesle Robert F. Newmyer Milan Nikolic Grigori Nikulin
Peter Jamison Otto Kahn Mikheil Kalatozishvili Ferenc Kardos István Kardos Kirin Kiki Julie Kirkham Werner Koenig Öscar Kramer Gulshan Kumar Franklin R. Levy Amilcar Lyra A.V. Meiyappan Robert de Nesle Robert f. Newmyer Milan Nikolic Grigori Nikulin
Peter Jamison Otto Kahn Mikheil Kalatozishvili Ferenc Kardos István Kardos Kirin Kiki Julie Kirkham Werner Koenig Öscar Kramer Gulshan Kumar Franklin R. Levy Amilcar Lyra A.V. Meiyappan Robert de Nesle Robert F. Newmyer Milan Nikolic Grigori Nikulin Nutan James Paris J.G. Patterson Jr. René Pignières
Peter Jamison Otto Kahn Mikheil Kalatozishvili Ferenc Kardos István Kardos Kirin Kiki Julie Kirkham Werner Koenig Öscar Kramer Gulshan Kumar Franklin R. Levy Amilcar Lyra A.V. Meiyappan Robert de Nesle Robert F. Newmyer Milan Nikolic Grigori Nikulin Nutan James Paris J.G. Patterson Jr. René Pignières John E. Quill
Peter Jamison Otto Kahn Mikheil Kalatozishvili Ferenc Kardos István Kardos Kirin Kiki Julie Kirkham Werner Koenig Öscar Kramer Gulshan Kumar Franklin R. Levy Amilcar Lyra A.V. Meiyappan Robert de Nesle Robert F. Newmyer Milan Nikolic Grigori Nikulin Nutan James Paris J.G. Patterson Jr. René Pignières John E. Quill Raoul N. Rizik
Peter Jamison Otto Kahn Mikheil Kalatozishvili Ferenc Kardos István Kardos Kirin Kiki Julie Kirkham Werner Koenig Öscar Kramer Gulshan Kumar Franklin R. Levy Amilcar Lyra A.V. Meiyappan Robert de Nesle Robert F. Newmyer Milan Nikolic Grigori Nikulin Nutan James Paris J.G. Patterson Jr. René Pignières John E. Quill Raoul N. Rizik Mark Rosenberg
Peter Jamison Otto Kahn Mikheil Kalatozishvili Ferenc Kardos István Kardos István Kardos Kirin Kiki Julie Kirkham Werner Koenig Öscar Kramer Gulshan Kumar Franklin R. Levy Amilcar Lyra A.V. Meiyappan Robert de Nesle Robert F. Newmyer Milan Nikolic Grigori Nikulin Nutan James Paris J.G. Patterson Jr. René Pignières John E. Quill Raoul N. Rizik Mark Rosenberg Micha Shagrir
Peter Jamison Otto Kahn Mikheil Kalatozishvili Ferenc Kardos István Kardos Kirin Kiki Julie Kirkham Werner Koenig Öscar Kramer Gulshan Kumar Franklin R. Levy Amilcar Lyra A.V. Meiyappan Robert de Nesle Robert F. Newmyer Milan Nikolic Grigori Nikulin Nutan James Paris J.G. Patterson Jr. René Pignières John E. Quill Raoul N. Rizik Mark Rosenberg Micha Shagrir Sándor Simó
Peter Jamison Otto Kahn Mikheil Kalatozishvili Ferenc Kardos István Kardos István Kardos Kirin Kiki Julie Kirkham Werner Koenig Öscar Kramer Gulshan Kumar Franklin R. Levy Amilcar Lyra A.V. Meiyappan Robert de Nesle Robert F. Newmyer Milan Nikolic Grigori Nikulin Nutan James Paris J.G. Patterson Jr. René Pignières John E. Quill Raoul N. Rizik Mark Rosenberg Micha Shagrir Sándor Simó Mary Craig Sinclair
Peter Jamison Otto Kahn Mikheil Kalatozishvili Ferenc Kardos István Kardos Kirin Kiki Julie Kirkham Werner Koenig Öscar Kramer Gulshan Kumar Franklin R. Levy Amilcar Lyra A.V. Meiyappan Robert de Nesle Robert F. Newmyer Milan Nikolic Grigori Nikulin Nutan James Paris J.G. Patterson Jr. René Pignières John E. Quill Raoul N. Rizik Mark Rosenberg Micha Shagrir Sándor Simó
Peter Jamison Otto Kahn Mikheil Kalatozishvili Ferenc Kardos István Kardos Kirin Kiki Julie Kirkham Werner Koenig Öscar Kramer Gulshan Kumar Franklin R. Levy Amilcar Lyra A.V. Meiyappan Robert de Nesle Robert F. Newmyer Milan Nikolic Grigori Nikulin Nutan James Paris J.G. Patterson Jr. René Pignières John E. Quill Raoul N. Rizik Mark Rosenberg Micha Shagrir Sándor Simó Mary Craig Sinclair Upton Sinclair Ivan Solovyov John Spotton
Peter Jamison Otto Kahn Mikheil Kalatozishvili Ferenc Kardos István Kardos Kirin Kiki Julie Kirkham Werner Koenig Öscar Kramer Gulshan Kumar Franklin R. Levy Amilcar Lyra A.V. Meiyappan Robert de Nesle Robert F. Newmyer Milan Nikolic Grigori Nikulin Nutan James Paris J.G. Patterson Jr. René Pignières John E. Quill Raoul N. Rizik Mark Rosenberg Micha Shagrir Sándor Simó Mary Craig Sinclair Upton Sinclair Ivan Solovyov John Spotton Dawn Steel
Peter Jamison Otto Kahn Mikheil Kalatozishvili Ferenc Kardos István Kardos István Kardos Kirin Kiki Julie Kirkham Werner Koenig Öscar Kramer Gulshan Kumar Franklin R. Levy Amilcar Lyra A.V. Meiyappan Robert de Nesle Robert F. Newmyer Milan Nikolic Grigori Nikulin Nutan James Paris J.G. Patterson Jr. René Pignières John E. Quill Raoul N. Rizik Mark Rosenberg Micha Shagrir Sándor Simó Mary Craig Sinclair Upton Sinclair Upton Sinclair Upton Spotton Dawn Steel Joe Strummer
Peter Jamison Otto Kahn Mikheil Kalatozishvili Ferenc Kardos István Kardos István Kardos Kirin Kiki Julie Kirkham Werner Koenig Öscar Kramer Gulshan Kumar Franklin R. Levy Amilcar Lyra A.V. Meiyappan Robert de Nesle Robert fe. Newmyer Milan Nikolic Grigori Nikulin Nutan James Paris J.G. Patterson Jr. René Pignières John E. Quill Raoul N. Rizik Mark Rosenberg Micha Shagrir Sándor Simó Mary Craig Sinclair Upton Sinclair Ivan Solovyov John Spotton Dawn Steel Joe Strummer Andreas Thiel
Peter Jamison Otto Kahn Mikheil Kalatozishvili Ferenc Kardos István Kardos István Kardos Kirin Kiki Julie Kirkham Werner Koenig Öscar Kramer Gulshan Kumar Franklin R. Levy Amilcar Lyra A.V. Meiyappan Robert de Nesle Robert F. Newmyer Milan Nikolic Grigori Nikulin Nutan James Paris J.G. Patterson Jr. René Pignières John E. Quill Raoul N. Rizik Mark Rosenberg Micha Shagrir Sándor Simó Mary Craig Sinclair Upton Sinclair Upton Sinclair Upton Spotton Dawn Steel Joe Strummer

Figure 18: Query 8 results

Home
See the results

Figure 19: Query 9 search parameter "input"

	Tido
Ruffala	Title  Bill and the Indians or Sitting Bull's History I assu
ounaio	Bill and the Indians, or Sitting Bull's History Lesso Quintet
	Inglourious Basterds
	Fargo
	The Big Lebowski
	Heat
	Awakenings
	Blow
	Where the Truth Lies  Devil's Knot
	Panic Room
	The Frighteners
	Red Corner
	Three Christs
	A Real Woman
	Hannibal
	Heaven & Earth
	The Package Under Siege
	The Fugitive
	Come Early Morning
	Mindhunters
	Bobby
	Chloe
	Scarface
	Carlito's Way  Batman Returns
	Dark Shadows
	Ghosts of Mississippi
	Present Tense, Past Perfect
	Havana
	Le grand bleu
	Beetlejuice
	Alter Ego
	One Small Step The Big Chill
	Ain't We Got Fun
	I Wanna Be a Sailor
	Little Red Walking Hood
	Picador Porky
	Porky's Duck Hunt
	Porky's Garden Cinderella Meets Fella
	Daffy Duck & Egghead
	Daffy Duck in Hollywood
	A Feud There Was
	The Mice Will Play
	Detouring America
	Screwball Football
	Cross Country Detaurs
	Cross Country Detours The Early Worm Gets the Bird
	A Gander at Mother Goose
	Woody Woodpecker and His Friends
	Pilot
	Penguin One, Us Zero
	Michael McKean/Chaka Khan/The Folksmen
	Ed Asner/The Kinks
	Household Saints
	Household Saints The Comedian
	Household Saints
	Household Saints The Comedian Ruthless People
	Household Saints The Comedian Ruthless People The Musketeer
	Household Saints The Comedian Ruthless People The Musketeer Zodiac
	Household Saints The Comedian Ruthless People The Musketeer Zodiac Lincoln The Color Purple Superman
	Household Saints The Comedian Ruthless People The Musketeer Zodiac Lincoln The Color Purple Superman Superman
	Household Saints The Comedian Ruthless People The Musketeer Zodiac Lincoln The Color Purple Superman Superman II Aria
	Household Saints The Comedian Ruthless People The Musketeer Zodiac Lincoln The Color Purple Superman Superman II Aria The Beautiful Deception
	Household Saints The Comedian Ruthless People The Musketeer Zodiac Lincoln The Color Purple Superman Superman II Aria The Beautiful Deception Stray Dogs
	Household Saints The Comedian Ruthless People The Musketeer Zodiac Lincoln The Color Purple Superman Superman II Aria The Beautiful Deception

Figure 20: Query 9 results

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## 10. List all the shows which have a total run time less than a particular value

Runtime in hours	10

Figure 21: Query 10 search parameter input

Tide	Runtime
Americana	30
America's Town Meeting	60
Author Meets the Critics	30
Break the Bank	30
Movieland Quiz	30
On the Corner	30
We, the People	30
Blind Date	30
The Eyes Have It	30
Easy Aces	15
Hold It Please	30
Kay Kyser's Kollege of Musical Knowledge	60
Leave It to the Girls	30
Stump the Authors	30
Sunday at Home	15
Think Fast	30
This Is Show Business	30
Abe Burrows' Almanac	30
American Forum of the Air	30
Answer Yes or No	30
Beat the Clock	30
By Popular Demand	30
Can You Top This	30
Chance of a Lifetime	30
The Faye Emerson Show	15
Pantomime Quiz	30
Penthouse Party	30
Star of the Family	30
Tala a Chanca	30

Figure 22: Query 10 results