Lecture 08-2: Advanced Statistics in SQL

DATA 503: Fundamentals of Data Engineering

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This lecture covers statistical functions built into SQL, including correlation, regression, ranking, and window functions. We use real U.S. Census and export data to explore how SQL can answer statistical questions without ever leaving the database. Based on Chapter 11 of Practical SQL, 2nd Edition.

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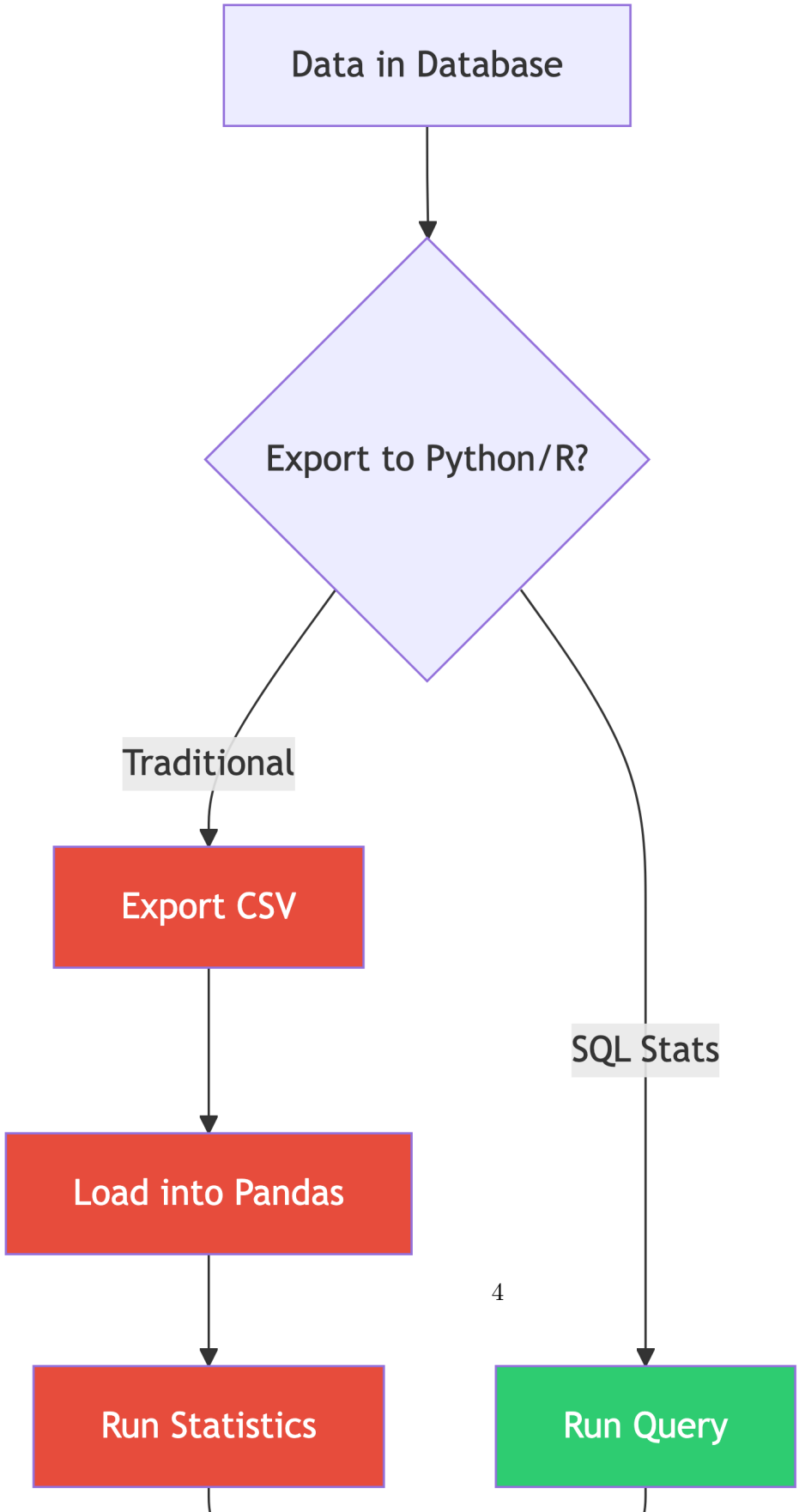
1 Advanced Statistics in SQL

Your database isn't just a filing cabinet. It's a statistics lab.

Today we discover that SQL has been hiding superpowers from you this whole time.

1.1 Why Statistics in SQL?

1.2 The Case for In-Database Stats



Why not just use Python/R?

- No data movement = faster iteration
- Stats computed where data lives
- Works on billions of rows without loading into memory
- Perfect for quick exploratory analysis

SQL statistical functions are **aggregate functions** on steroids

Standard ANSI SQL (including PostgreSQL) includes powerful stats functions. You don't need to leave the database!

1.3 What SQL Gives You

Category	Functions
Correlation	`corr(Y, X)`
Regression	`regr_slope()`, `regr_intercept()`, `regr_r2()`
Spread	`var_pop()`, `stddev_pop()`, `var_samp()`, `stddev_samp()`
Ranking	`rank()`, `dense_rank()`, `row_number()`
Windows	`OVER()`, `PARTITION BY`, frame clauses

That's a full intro stats course hiding in your database engine.

2 Setting Up: Follow Along

2.1 Loading the Data

2.2 The Data Files

All data files live in the `ch11/` folder. Here's what we're working with:

File	What It Contains
`acs_2014_2018_stats.csv`	American Community Survey: education, income, commute data for every US county
`cbp_naics_72_establishments.csv`	County Business Patterns: restaurant/hotel counts per county
`us_exports.csv`	Monthly US citrus and soybean export values (2002-2020)

We'll load these as we go. First up: the ACS data.

2.3 Step 1: Create the ACS Table

```
CREATE TABLE acs_2014_2018_stats (
    geoid text CONSTRAINT geoid_key PRIMARY KEY,
    county text NOT NULL,
    st text NOT NULL,
    pct_travel_60_min numeric(5,2),
    pct_bachelors_higher numeric(5,2),
    pct_masters_higher numeric(5,2),
    median_hh_income integer,
    CHECK (pct_masters_higher <= pct_bachelors_higher)
);
```

That `CHECK` constraint is doing real work: it ensures the master's percentage never exceeds the bachelor's percentage. If your import violates this, you've got a data quality problem.

2.4 Step 2: Import the CSV

Use `\copy` in psql (update the path to wherever your files live):

```
\copy acs_2014_2018_stats
FROM '/your/path/to/ch11/acs_2014_2018_stats.csv'
WITH (FORMAT CSV, HEADER);
```

> **Heads Up: Column Names**
>
> The CSV headers use shortened names (`pct_bach_higher`, `med_hh_inc`). If you get a column mismatch error, either rename the columns in the `CREATE TABLE` to match the CSV, or use a staging table. Quick check after import:
>
> ```
> SELECT * FROM acs_2014_2018_stats LIMIT 5;
> ```

2.5 Sanity Check

```
SELECT count(*) FROM acs_2014_2018_stats;
-- Should return 3,142 (one row per US county)
```

Every county in America is now in your database. All **3,142** of them.

2.6 What's In the ACS Data?

Column	What It Measures
`pct_travel_60_min`	% of workers ages 16+ with 60+ minute commute
`pct_bachelors_higher`	% of people ages 25+ with bachelor's degree or higher
`pct_masters_higher`	% of people ages 25+ with master's degree or higher
`median_hh_income`	Median household income (2018 inflation-adjusted dollars)

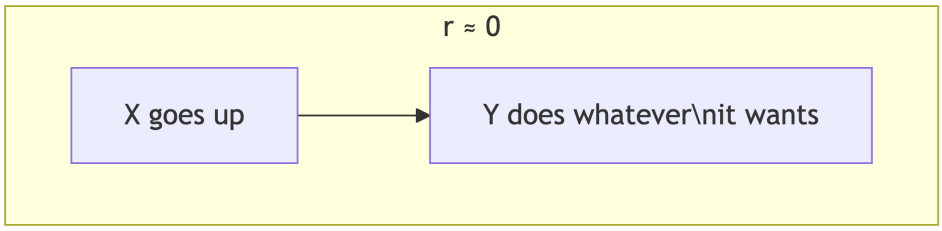
The big question: **Does education really pay?**

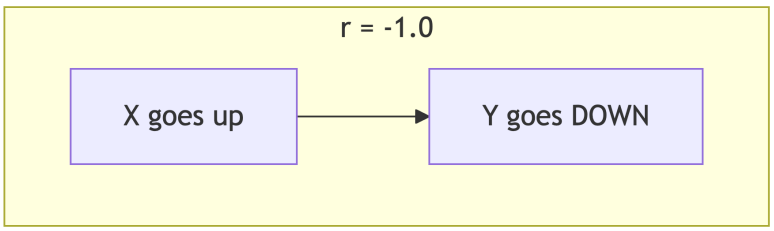
Let's find out with math.

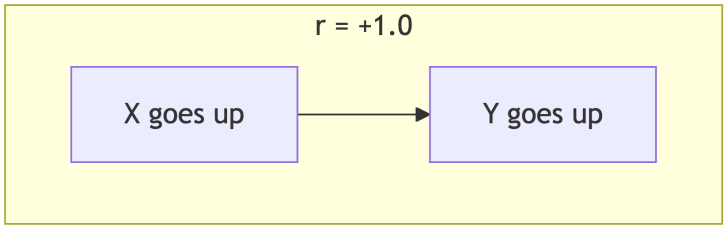
3 Correlation: Finding Relationships

3.1 Measuring Correlation

3.2 What Is Correlation?







The **Pearson correlation coefficient** (r) measures the strength and direction of a linear relationship between two variables.

r Value	Interpretation
0	No relationship
.01 to .29	Weak
.30 to .59	Moderate
.60 to .99	Strong to nearly perfect
1	Perfect

Same ranges apply for negative values (inverse relationship).

3.3 The corr(Y, X) Function

SQL's `corr()` is a **binary aggregate function**: it takes two inputs.

- **Y** = dependent variable (what you're measuring)
- **X** = independent variable (what you think influences Y)

```
SELECT corr(median_hh_income, pct_bachelors_higher)
    AS bachelors_income_r
FROM acs_2014_2018_stats;
```

Result:

```
bachelors_income_r
------------------
0.6999086502599159
```

That's **r 0.70**, a **strong positive correlation**. Counties with more bachelor's degrees tend to have higher median incomes. Stay in school, kids.

3.4 Comparing Multiple Correlations

Let's check several relationships at once and round for readability:

```sql
SELECT
    round(
      corr(median_hh_income, pct_bachelors_higher)::numeric, 2
    ) AS bachelors_income_r,
    round(
      corr(pct_travel_60_min, median_hh_income)::numeric, 2
    ) AS income_travel_r,
    round(
      corr(pct_travel_60_min, pct_bachelors_higher)::numeric, 2
    ) AS bachelors_travel_r
FROM acs_2014_2018_stats;
```

Relationship	r	What It Means
Education → Income	0.70	Strong: more degrees = more money
Income → Long Commute	0.06	Basically nothing
Education → Long Commute	-0.14	Weak inverse: more education, slightly less commuting

Money doesn't make your commute longer. That's a relief.

Why `::numeric`?

`corr()` returns a `double precision` float. We cast to `numeric` so `round()` can accept it. This is PostgreSQL-specific syntax.

3.5 The Big Caveat

Correlation Causation!

A strong correlation tells you two things **move together**. It does NOT tell you one **causes** the other.
Classic example: ice cream sales and drowning deaths are highly correlated. That doesn't mean ice cream kills people. (They're both driven by hot weather.)
Check out tylervigen.com/spurious-correlations for hilariously absurd correlations, like the divorce rate in Maine correlating with margarine consumption.

3.6 Knowledge Check: Correlation

> **Try It Yourself!**
>
> 1. What is the correlation between `pct_masters_higher` and `median_hh_income`? Is it **higher** or **lower** than the bachelor's correlation? What might explain the difference?
> 2. If `corr()` returns `-0.45`, what does that tell you about the relationship between the two variables?
> 3. Does switching the order of inputs in `corr()` change the result? Try it!

3.7 Solution 1: Masters vs. Income Correlation

Step 1: Write the query, swapping `pct_bachelors_higher` for `pct_masters_higher`:

```
SELECT round(
    corr(median_hh_income, pct_masters_higher)::numeric, 2
) AS masters_income_r
FROM acs_2014_2018_stats;
```

Step 2: Compare the result:

Variable	r
Bachelor's	0.70
Master's	~0.60

The master's correlation is **lower**. Why? Fewer people hold master's degrees, so there's less variation in that column across counties. Less variation = weaker signal for the correlation to pick up on. Also, master's degree holders are a subset of bachelor's degree holders, so the bachelor's measure captures a broader (and more predictive) slice of educational attainment.

3.8 Solution 2: Interpreting r = -0.45

Step 1: Check the sign. Negative = **inverse relationship**.

Step 2: Check the magnitude. 0.45 falls in the **moderate** range (0.30 to 0.59).

Answer: A correlation of -0.45 tells you there's a **moderate inverse relationship**: as one variable increases, the other tends to decrease. Not a strong lock-step decline, but a clear pattern.

3.9 Solution 3: Does Input Order Matter?

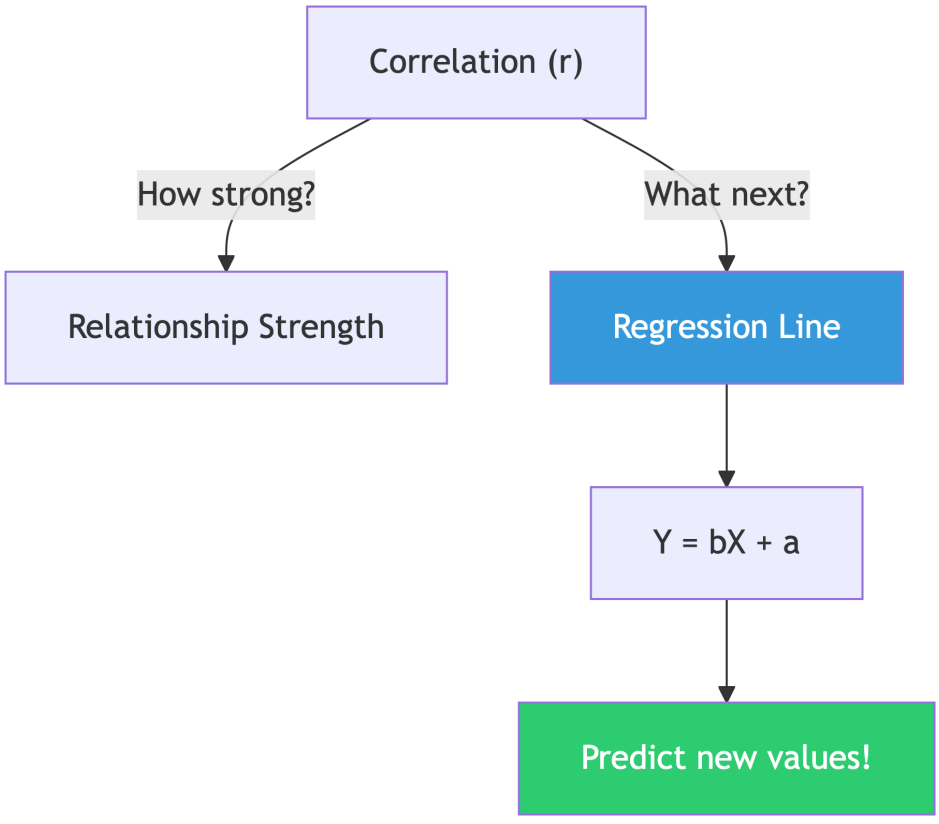
```sql
-- Original order
SELECT corr(median_hh_income, pct_bachelors_higher) AS original;

-- Swapped order
SELECT corr(pct_bachelors_higher, median_hh_income) AS swapped;
```

Answer: Both return the **same value** (~0.70). Correlation is symmetric: `corr(Y, X) = corr(X, Y)`. The function signature says Y, X for convention (matching regression), but the math doesn't care about order.

4 Regression: Predicting Values

4.1 Linear Regression in SQL

4.2 From Correlation to Prediction



Correlation tells you **if** a relationship exists.

Regression gives you the **equation** to make predictions.

$\mathbf{Y = bX + a}$ (the least squares regression line)

- **b** = slope (`regr_slope`) — how much Y changes per unit of X
- **a** = y-intercept (`regr_intercept`) — Y value when X is zero
- **Y** = dependent variable (predicted value)
- **X** = independent variable (known value)

4.3 Computing Slope and Intercept

Given bachelor's degree percentage, predict median income:

```
SELECT
    round(
        regr_slope(median_hh_income, pct_bachelors_higher)::numeric, 2
    ) AS slope,
    round(
        regr_intercept(median_hh_income, pct_bachelors_higher)::numeric, 2
    ) AS y_intercept
FROM acs_2014_2018_stats;
```

Result:

```
 slope     y_intercept
-------   -----------
1016.55     29651.42
```

Translation: For every 1% increase in bachelor's degree holders, median income goes up by about **$1,016.55**

4.4 Using the Equation

Our regression line: $\mathbf{Y = 1016.55X + 29{,}651.42}$

What income would we predict for a county where **30%** have bachelor's degrees?

```
Y = 1016.55(30) + 29,651.42
Y = 30,496.50 + 29,651.42
Y = 60,147.92
```

We'd predict a median household income of about **$60,148**.

That's the power of regression: turning known data into predictions about data you haven't seen yet.

4.5 R-Squared: How Good Is the Fit?

The **coefficient of determination** (R^2) tells us what percentage of variation in Y is explained by X:

```
SELECT round(
    regr_r2(median_hh_income, pct_bachelors_higher)::numeric, 3
) AS r_squared
FROM acs_2014_2018_stats;
```

Result:

```
r_squared
---------
    0.490
```

$R^2 = 0.490$ means education explains about **49%** of the variation in median household income across counties.

That's solid for a single variable! But 51% is explained by other factors: cost of living, industry mix, geography, etc. Real-world data is messy.

4.6 Knowledge Check: Regression

> **Try It Yourself!**
>
> 1. Use `regr_slope` and `regr_intercept` with **`pct_masters_higher`** as the X variable. How does the slope compare to the bachelor's version?
> 2. Calculate R^2 for masters vs. income. Does a master's degree predict income better than a bachelor's?
> 3. Using the bachelor's regression equation, predict income for a county with **50%** bachelor's holders. Does it seem realistic? What are the limits of this approach?

4.7 Solution 1: Master's Regression

Step 1: Swap in `pct_masters_higher` as the X variable:

```
SELECT
    round(regr_slope(median_hh_income, pct_masters_higher)::numeric, 2) AS slope,
    round(regr_intercept(median_hh_income, pct_masters_higher)::numeric, 2) AS y_intercept
FROM acs_2014_2018_stats;
```

Step 2: Compare slopes:

X Variable	Slope	Meaning
Bachelor's	1,016.55	Each 1% more bachelor's = +$1,017 income
Master's	~2,000+	Each 1% more master's = +$2,000+ income

The master's slope is **steeper**! That makes sense: master's degrees are rarer, so each percentage point of increase represents a bigger shift in a county's educational profile. The "per unit" impact is larger, but there are fewer units to work with.

4.8 Solution 2: R^2 Comparison

```
SELECT
    round(regr_r2(median_hh_income, pct_bachelors_higher)::numeric, 3) AS r2_bachelors,
    round(regr_r2(median_hh_income, pct_masters_higher)::numeric, 3) AS r2_masters
FROM acs_2014_2018_stats;
```

Variable	R^2	% Explained
Bachelor's	0.490	49%
Master's	~0.360	~36%

Bachelor's degree percentage is the **better predictor**. It explains about 49% of income variation vs. ~36% for master's. More data points, more variation, more predictive power.

4.9 Solution 3: Predicting at 50%

Step 1: Plug X = 50 into our equation:

```
Y = 1016.55(50) + 29,651.42
Y = 50,827.50 + 29,651.42
Y = 80,478.92
```

Step 2: Does ~$80,479 seem realistic? It's high but plausible for a highly educated county (think: suburban counties near DC or San Francisco).

Step 3: The limits:

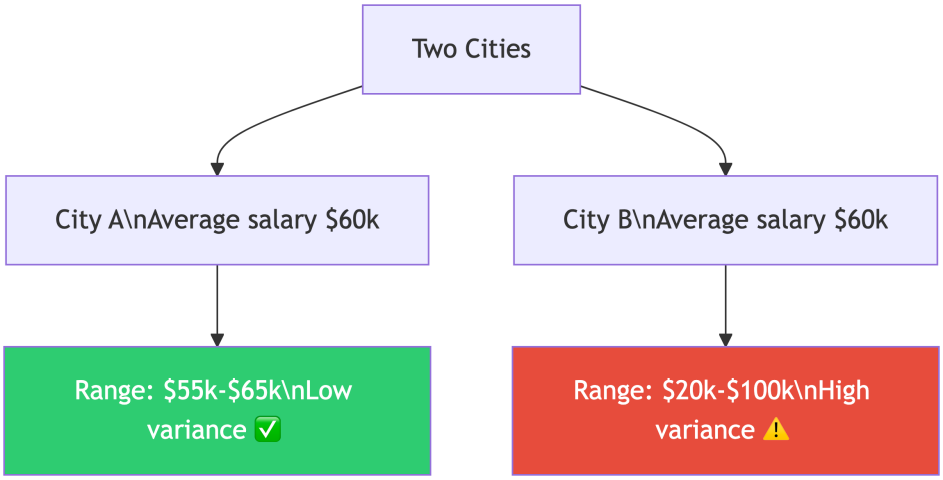
- We're **extrapolating** beyond most of our data (few counties hit 50%)
- Linear regression assumes a straight line forever, but reality has diminishing returns
- Other factors (cost of living, industry) aren't in the model
- The R^2 of 0.49 means 51% of variation is unexplained!

Regression is a flashlight, not a crystal ball.

5 Variance and Standard Deviation

5.1 Measuring Spread

5.2 Why Spread Matters



Same average, wildly different stories.

- **Variance** = average of squared deviations from the mean (different units!)
- **Standard deviation** = square root of variance (same units as data)

Function	What
`var_pop()`	Population variance
`var_samp()`	Sample variance
`stddev_pop()`	Population std dev
`stddev_samp()`	Sample std dev

5.3 Population vs. Sample

When to Use Which?

- **Population** (`_pop`): Your data IS the entire population. We have *all* 3,142 US counties, so we use population functions.
- **Sample** (`_samp`): Your data is a subset of a larger population, like a random survey of 500 counties.

Standard deviation is expressed in the **same units** as your data. Variance is not. It's on its own scale, which is larger than the original units.

5.4 Computing Spread

```sql
-- Population variance of median household income
SELECT var_pop(median_hh_income)
FROM acs_2014_2018_stats;

-- Population standard deviation
SELECT stddev_pop(median_hh_income)
FROM acs_2014_2018_stats;
```

Think about what the standard deviation tells you: in a normal distribution, about **two-thirds** of values fall within one standard deviation of the mean, and **95%** within two standard deviations.

If mean income is ~$50k and std dev is ~$12k, most counties fall between ~$38k and ~$62k.

5.5 Knowledge Check: Spread

> **Think About It**
>
> 1. Compute `stddev_pop` for both `pct_bachelors_higher` and `pct_masters_higher`. Which has more variation across counties?
> 2. If the standard deviation of income is ~$12,000 and the mean is ~$50,000, roughly what range contains the middle 95% of counties? (Hint: 2 standard deviations)
> 3. When would you use `var_samp` instead of `var_pop`? Give a real-world example.

5.6 Solution 1: Comparing Variation

Step 1: Run both in one query:

```
SELECT
    round(stddev_pop(pct_bachelors_higher)::numeric, 2) AS stddev_bachelors,
    round(stddev_pop(pct_masters_higher)::numeric, 2) AS stddev_masters
FROM acs_2014_2018_stats;
```

Step 2: Compare the results:

Variable	Std Dev
Bachelor's	~9.0
Master's	~4.0

Bachelor's percentage has **more variation** across counties. That makes sense: the range of bachelor's attainment across US counties is much wider (some rural counties under 10%, some suburban counties over 60%) compared to master's degrees which cluster in a narrower range.

5.7 Solution 2: The 95% Range

Step 1: Recall the rule: in a normal distribution, ~95% of values fall within **2 standard deviations** of the mean.

Step 2: Calculate the range:

```
Lower bound = $50,000 - (2 × $12,000) = $26,000
Upper bound = $50,000 + (2 × $12,000) = $74,000
```

Answer: Roughly 95% of US counties have a median household income between **$26,000 and $74,000**. Counties outside this range are the outliers (very poor rural areas or very wealthy suburbs).

5.8 Solution 3: Population vs. Sample

Use `var_samp` / `stddev_samp` when your data is a sample, not the whole population.

Real-world examples:

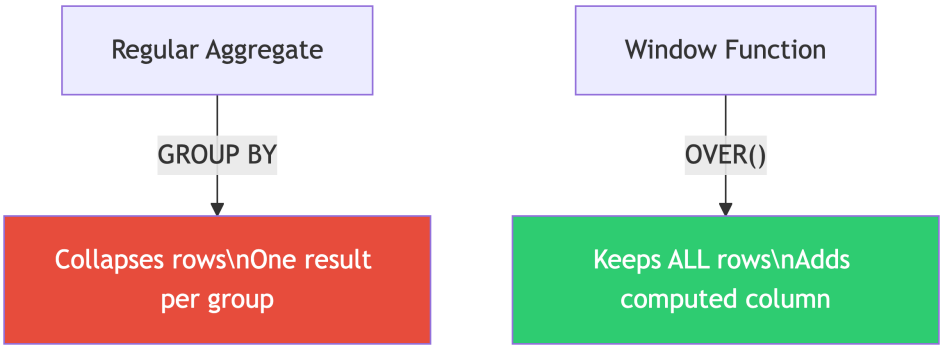
- You survey **500 random customers** out of 50,000 total → sample functions
- You poll **200 students** from a university of 5,000 → sample functions
- You analyze **all 3,142 US counties** → population functions (that IS the whole population)

The difference: sample functions use **N-1** in the denominator (Bessel's correction) to account for the fact that a sample tends to underestimate the true population variance. With large N, the difference is tiny. With small samples, it matters!

6 Ranking with Window Functions

6.1 rank() and dense_rank()

6.2 Window Functions: The Big Idea



Aggregate functions collapse rows into summaries.

Window functions compute values across rows **without** collapsing them.

The magic keyword: `OVER()`

Think of it as: "compute this, but looking through a window at related rows." The query first generates the result set, then the window function runs across it.

6.3 Setting Up the Widget Data

```sql
CREATE TABLE widget_companies (
    id integer PRIMARY KEY GENERATED ALWAYS AS IDENTITY,
    company text NOT NULL,
    widget_output integer NOT NULL
);

INSERT INTO widget_companies (company, widget_output)
VALUES
    ('Dom Widgets', 125000),
    ('Ariadne Widget Masters', 143000),
    ('Saito Widget Co.', 201000),
    ('Mal Inc.', 133000),
    ('Dream Widget Inc.', 196000),
    ('Miles Amalgamated', 620000),
    ('Arthur Industries', 244000),
    ('Fischer Worldwide', 201000);
```

Yes, those are Inception references. Christopher Nolan approves.

6.4 rank() vs dense_rank()

```sql
SELECT
    company,
    widget_output,
    rank() OVER (ORDER BY widget_output DESC),
    dense_rank() OVER (ORDER BY widget_output DESC)
FROM widget_companies
ORDER BY widget_output DESC;
```

6.5 The Results: Spot the Difference

company	widget_output	rank	dense_rank
Miles Amalgamated	620,000	1	1
Arthur Industries	244,000	2	2
Saito Widget Co.	**201,000**	**3**	**3**

company	widget_output	rank	dense_rank
Fischer Worldwide	**201,000**	**3**	**3**
Dream Widget Inc.	196,000	**5**	**4**
Ariadne Widget Masters	143,000	6	5
Mal Inc.	133,000	7	6
Dom Widgets	125,000	8	7

After the tie at rank 3:

- `rank()` **skips** to 5 (there are 4 companies ahead of Dream Widget)
- `dense_rank()` continues to 4 (no gaps, 3 distinct output levels ahead)

6.6 When to Use Which?

Use Case	Function	Why
Competition rankings (Olympics)	`rank()`	Two golds, no silver
Top-N distinct levels	`dense_rank()`	Exactly N unique levels
Unique row numbering	`row_number()`	No ties, ever

In practice, `rank()` is used most often. It more accurately reflects the total number of items ranked ahead of a given row.

7 PARTITION BY: Ranking Within Groups

7.1 Grouped Rankings

7.2 The Store Sales Data

```
CREATE TABLE store_sales (
    store text NOT NULL,
    category text NOT NULL,
    unit_sales bigint NOT NULL,
    CONSTRAINT store_category_key PRIMARY KEY (store, category)
);

INSERT INTO store_sales (store, category, unit_sales)
VALUES
    ('Broders', 'Cereal', 1104),
```

```
    ('Wallace', 'Ice Cream', 1863),
    ('Broders', 'Ice Cream', 2517),
    ('Cramers', 'Ice Cream', 2112),
    ('Broders', 'Beer', 641),
    ('Cramers', 'Cereal', 1003),
    ('Cramers', 'Beer', 640),
    ('Wallace', 'Cereal', 980),
    ('Wallace', 'Beer', 988);
```

Three stores. Three product categories. Who's winning in each category?

7.3 Ranking Within Each Category

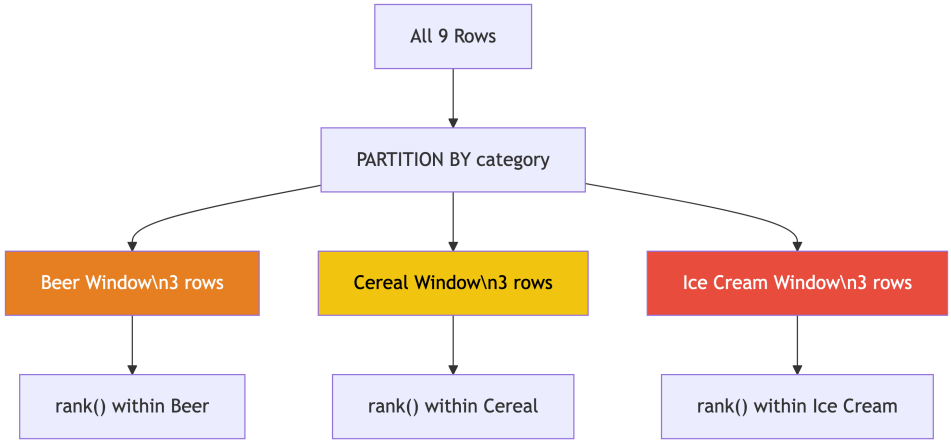
```
SELECT
    category,
    store,
    unit_sales,
    rank() OVER (PARTITION BY category ORDER BY unit_sales DESC)
FROM store_sales
ORDER BY category, rank() OVER (
    PARTITION BY category ORDER BY unit_sales DESC
);
```

7.4 The Results

category	store	unit_sales	rank
Beer	Wallace	988	1
Beer	Broders	641	2
Beer	Cramers	640	3
Cereal	Broders	1104	1
Cereal	Cramers	1003	2
Cereal	Wallace	980	3
Ice Cream	Broders	2517	1
Ice Cream	Cramers	2112	2
Ice Cream	Wallace	1863	3

`PARTITION BY` restarts the ranking for each category. Broders dominates cereal and ice cream, but Wallace takes the beer crown!

7.5 How PARTITION BY Works



`PARTITION BY` creates **separate windows** for each group.

- Each partition gets its own ranking
- Rows outside the partition are invisible
- Original rows are preserved (not collapsed!)

Template:

```
function() OVER (
    PARTITION BY grouping_col
    ORDER BY sorting_col DESC
)
```

You can apply this pattern everywhere: rank employees by salary within each department, movies by revenue within each genre, students by GPA within each major…

7.6 Knowledge Check: Ranking

> **Try It Yourself!**
>
> 1. Write a query that finds **only the #1 ranked store** in each category. (Hint: wrap the ranking query in a subquery or CTE and filter with `WHERE rank = 1`)
> 2. What would happen if you **removed** `PARTITION BY` from the query? Try it!
> 3. Add `row_number()` alongside `rank()` in the widget companies query. How does `row_number()` handle the tie between Saito and Fischer?

7.7 Solution 1: Top Store Per Category

Step 1: We can't filter on a window function directly in `WHERE` (it hasn't been computed yet). So we wrap it in a **subquery** or **CTE**:

```
-- Using a CTE (Common Table Expression)
WITH ranked AS (
    SELECT
        category,
        store,
        unit_sales,
        rank() OVER (PARTITION BY category ORDER BY unit_sales DESC) AS rnk
    FROM store_sales
)
SELECT category, store, unit_sales
FROM ranked
WHERE rnk = 1
ORDER BY category;
```

Step 2: The result:

category	store	unit_sales
Beer	Wallace	988
Cereal	Broders	1104
Ice Cream	Broders	2517

This is a **very common pattern**: CTE with window function → filter in outer query. You'll use this all the time.

7.8 Solution 2: Without PARTITION BY

Step 1: Remove `PARTITION BY`:

```
SELECT category, store, unit_sales,
    rank() OVER (ORDER BY unit_sales DESC) AS overall_rank
FROM store_sales
ORDER BY overall_rank;
```

Step 2: Now ALL 9 rows compete against each other in a single ranking:

category	store	unit_sales	overall_rank
Ice Cream	Broders	2517	1
Ice Cream	Cramers	2112	2
Ice Cream	Wallace	1863	3
Cereal	Broders	1104	4
...	...	...	...

Without `PARTITION BY`, ice cream dominates the top because those sales numbers are bigger overall. The category-level insight is lost. That's why we partition!

7.9 Solution 3: row_number() and Ties

Step 1: Add `row_number()` to the widget query:

```
SELECT company, widget_output,
    rank() OVER (ORDER BY widget_output DESC),
    dense_rank() OVER (ORDER BY widget_output DESC),
    row_number() OVER (ORDER BY widget_output DESC)
FROM widget_companies
ORDER BY widget_output DESC;
```

Step 2: Look at the tied companies (201,000):

company	rank	dense_rank	row_number
Saito Widget Co.	3	3	**3**
Fischer Worldwide	3	3	**4**

`row_number()` assigns **unique numbers** even for ties. One gets 3, the other gets 4. Which one gets which? It's **arbitrary** (the database picks). If you need deterministic tie-breaking, add more columns to the `ORDER BY`.

8 Rates: Meaningful Comparisons

8.1 Calculating Rates

8.2 Raw Counts Lie

Texas had **377,599** babies born in 2019. Utah had **46,826**. So Texas women have more babies, right?

Not so fast. Texas had **9x** the population of Utah.

The fertility rate (births per 1,000 women ages 15-44):

- Texas: **62.5**
- Utah: **66.7**

Utah actually had a higher birth rate! **Always normalize by population.**

8.3 Loading the Business Pattern Data

```
CREATE TABLE cbp_naics_72_establishments (
    state_fips text,
    county_fips text,
    county text NOT NULL,
    st text NOT NULL,
    naics_2017 text NOT NULL,
    naics_2017_label text NOT NULL,
    year smallint NOT NULL,
    establishments integer NOT NULL,
    CONSTRAINT cbp_fips_key PRIMARY KEY (state_fips, county_fips)
);

\copy cbp_naics_72_establishments
FROM '/your/path/to/ch11/cbp_naics_72_establishments.csv'
WITH (FORMAT CSV, HEADER);
```

This is **NAICS code 72**: Accommodation and Food Services (hotels, restaurants, bars). A good proxy for tourism activity.

8.4 Business Rates Per Capita

```
SELECT
    cbp.county,
    cbp.st,
    cbp.establishments,
    pop.pop_est_2018,
    round(
        (cbp.establishments::numeric / pop.pop_est_2018) * 1000, 1
    ) AS estabs_per_1000
FROM cbp_naics_72_establishments cbp
    JOIN us_counties_pop_est_2019 pop
    ON cbp.state_fips = pop.state_fips
```

```
    AND cbp.county_fips = pop.county_fips
WHERE pop.pop_est_2018 >= 50000
ORDER BY cbp.establishments::numeric / pop.pop_est_2018 DESC;
```

> **Note**
>
> This requires the `us_counties_pop_est_2019` table from Chapter 5. If you don't have it loaded, focus on the **pattern**: normalize by population to compare fairly.

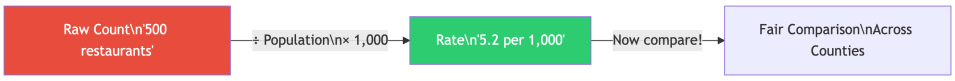
8.5 Top Tourism Counties

county	st	establishments	pop_est_2018	estabs_per_1000
Cape May County	New Jersey	925	92,446	10.0
Worcester County	Maryland	453	51,960	8.7
Monroe County	Florida	540	74,757	7.2
Warren County	New York	427	64,215	6.6
New York County	New York	10,428	1,629,055	6.4

Cape May = beach resorts. Worcester County = Ocean City. Monroe County = Florida Keys.

New York County (Manhattan) has a massive raw count, but it's only #5 per capita!

8.6 The Pattern: Rates, Not Counts



Always normalize when comparing across groups of different sizes.

The formula: `(count / population) × 1,000`

Real-world applications everywhere:

- Crime **rates** vs. crime counts
- COVID cases **per 100k** vs. raw cases
- Revenue **per employee** vs. total revenue
- Library visits **per capita** vs. total visits

Raw numbers mislead. Rates tell truth.

9 Rolling Averages: Smoothing Noisy Data

9.1 Window Frames

9.2 Loading Export Data

```
CREATE TABLE us_exports (
    year smallint,
    month smallint,
    citrus_export_value bigint,
    soybeans_export_value bigint
);

\copy us_exports
FROM '/your/path/to/ch11/us_exports.csv'
WITH (FORMAT CSV, HEADER);
```

Monthly US citrus and soybean export values from 2002 through 2020. Both are seasonal commodities tied to growing seasons.

9.3 The Problem With Raw Monthly Data

```
SELECT year, month, citrus_export_value
FROM us_exports
ORDER BY year, month;
```

Citrus exports are **wildly seasonal**: huge spikes in winter (growing season paused in the northern hemisphere, so countries need imports), dips in summer.

The monthly numbers bounce all over the place. How do you see the long-term trend through all that noise?

Answer: smooth it out with a rolling average!

9.4 The Hammer Store Example

Before we hit the real data, here's the intuition:

Date	Hammer Sales	7-Day Avg
May 1	0	
May 2	20	
May 3	15	

Date	Hammer Sales	7-Day Avg
May 4	3	
May 5	6	
May 6	1	
May 7	1	**6.6**
May 8	2	**6.9**
May 9	18	6.6
May 10	13	6.3

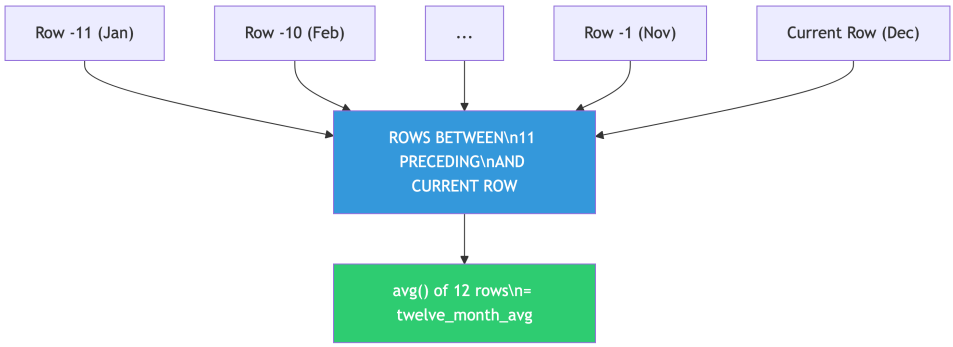
Daily sales bounce between 0 and 20. The 7-day average? Steady around 6-7. **That's the trend.**

9.5 The 12-Month Rolling Average

```sql
SELECT year, month, citrus_export_value,
    round(
       avg(citrus_export_value)
            OVER(ORDER BY year, month
                 ROWS BETWEEN 11 PRECEDING AND CURRENT ROW), 0
    ) AS twelve_month_avg
FROM us_exports
ORDER BY year, month;
```

This computes the average of the **current row plus the 11 rows before it** (12 months total). The window slides forward one row at a time.

9.6 Breaking Down the Window Frame



The `OVER()` clause defines the **window frame**:

- `ORDER BY year, month` — chronological order
- `ROWS BETWEEN 11 PRECEDING AND CURRENT ROW` — 12-row window

As you move through the data, the window **slides** along. Hence "rolling" average.

Other useful frames:

Frame	Effect
`ROWS BETWEEN 2 PRECEDING AND 2 FOLLOWING`	Centered 5-row window
`ROWS UNBOUNDED PRECEDING`	Running total from start
`ROWS BETWEEN 6 PRECEDING AND CURRENT ROW`	7-day rolling window

9.7 Why 12 Months?

Because citrus exports have a **12-month seasonal cycle**. A 12-month window cancels out the seasonal pattern and reveals the underlying trend.

> Choosing Your Window Size
>
> Match the window to the cycle length:
>
> - **Monthly seasonal data** → 12-month window
> - **Daily data with weekly patterns** → 7-day window
> - **Quarterly data** → 4-quarter window
>
> And a warning: missing time periods will throw off your averages! A missing month turns a 12-month average into a 13-month average because window functions count **rows**, not dates.

9.8 Sample Output

```
year month citrus_export_value twelve_month_avg
---- ----- ------------------- ----------------
2019     9            14012305         74465440
2019    10            26308151         74756757
2019    11            60885676         74853312
2019    12            84873954         74871644
2020     1           110924836         75099275
2020     2           171767821         78874520
2020     3           201231998         79593712
2020     4           122708243         78278945
```

Monthly values bounce between $14M and $201M. The 12-month average? Steady around $75M-$79M. **Trend revealed.**

9.9 Beyond Averages: Rolling Sums

You can swap `avg()` for `sum()` to get rolling totals:

```
SELECT year, month, citrus_export_value,
    sum(citrus_export_value)
        OVER(ORDER BY year, month
             ROWS BETWEEN 11 PRECEDING AND CURRENT ROW)
    AS twelve_month_sum
FROM us_exports
ORDER BY year, month;
```

A 12-month rolling sum gives you the annual total ending on any given month. Great for year-over-year comparisons without waiting for December!

9.10 Knowledge Check: Window Functions

> **Try It Yourself!**
>
> 1. Modify the rolling average query to use **`soybeans_export_value`** instead of citrus. Do soybeans show the same seasonal pattern? (Hint: soybeans have a different growing season)
> 2. Change the window to `ROWS BETWEEN 5 PRECEDING AND CURRENT ROW` (6-month average). How does a shorter window affect the smoothing?
> 3. Write a query that shows a **running total** of citrus exports using `ROWS UNBOUNDED PRECEDING`. What does this represent?

9.11 Solution 1: Soybeans Rolling Average

Step 1: Swap the column name:

```
SELECT year, month, soybeans_export_value,
    round(
       avg(soybeans_export_value)
            OVER(ORDER BY year, month
                 ROWS BETWEEN 11 PRECEDING AND CURRENT ROW), 0
```

```
    ) AS twelve_month_avg
FROM us_exports
ORDER BY year, month;
```

Step 2: Compare the patterns:

- **Citrus** peaks in winter (Dec-Mar) when northern hemisphere demand is high
- **Soybeans** peak in fall (Oct-Dec) right after the US harvest season

Both are seasonal, but with **different cycles**. The 12-month rolling average smooths both effectively because both have roughly annual patterns. The trend lines tell different economic stories: soybean exports surged due to trade dynamics, while citrus stayed relatively stable.

9.12 Solution 2: Shorter Window

Step 1: Change the frame to 6 months:

```
SELECT year, month, citrus_export_value,
    round(
       avg(citrus_export_value)
            OVER(ORDER BY year, month
                 ROWS BETWEEN 5 PRECEDING AND CURRENT ROW), 0
    ) AS six_month_avg
FROM us_exports
ORDER BY year, month;
```

Step 2: What changes?

Window	Smoothing Effect
12-month	Very smooth, seasonal pattern fully canceled
6-month	Bumpy, seasonal peaks still visible

A **shorter window** captures less than one full seasonal cycle, so the seasonal ups and downs bleed through. A 6-month average in citrus data still shows winter highs and summer lows, just dampened. You want your window to match (or exceed) the cycle length.

9.13 Solution 3: Running Total

Step 1: Use `sum()` with `ROWS UNBOUNDED PRECEDING`:

```
SELECT year, month, citrus_export_value,
    sum(citrus_export_value)
        OVER(ORDER BY year, month
             ROWS UNBOUNDED PRECEDING)
    AS running_total
FROM us_exports
ORDER BY year, month;
```

Step 2: What does this represent?

`ROWS UNBOUNDED PRECEDING` means "from the very first row to the current row." So each row shows the **cumulative total** of all citrus exports from January 2002 up to that month.

Step 3: Why is this useful?

- Track cumulative revenue or spending over time
- See when you hit milestones ("When did total exports cross $10 billion?")
- Compare cumulative performance across years

The running total only goes up (assuming positive values), creating a staircase pattern. The slope of that staircase is the trend. Steeper = faster growth.

10 Putting It All Together

10.1 Summary

10.2 Your SQL Statistics Toolkit

Tool	Function	Question It Answers
`corr(Y, X)`	Correlation	"Are these related?"
`regr_slope()` / `regr_intercept()`	Regression	"Can I predict Y from X?"
`regr_r2()`	R-squared	"How good is my prediction?"
`var_pop()` / `stddev_pop()`	Spread	"How spread out is the data?"
`rank()` / `dense_rank()`	Ranking	"What's the order?"

Tool	Function	Question It Answers
`PARTITION BY`	Grouped windows	"Rank within each group"
`ROWS BETWEEN ... AND ...`	Frame clause	"Smooth or accumulate over time"

10.3 When to Use SQL Stats vs. External Tools

SQL is great for:

- Quick exploratory analysis
- Data already in the database
- Simple correlations and regressions
- Ranking and top-N queries
- Rolling averages and running totals
- First pass before deeper analysis

Use Python/R when you need:

- Multiple regression and ML models
- Publication-quality visualizations
- Hypothesis testing with p-values
- Non-linear relationship modeling
- Custom statistical methods
- Significance testing

SQL gets you **80% of the insight for 20% of the effort**. That's a trade worth making.

10.4 Final Challenge

! Comprehensive Analysis

Using the `acs_2014_2018_stats` table, write queries that:

1. Find the **correlation** between `pct_masters_higher` and `median_hh_income`
2. Compute the **regression equation** to predict income from master's degree percentage
3. Calculate $\mathbf{R^2}$ for this relationship
4. **Rank** all states by their average median household income (you'll need `GROUP BY` + `rank() OVER()`)
5. For each state, show the **standard deviation** of income across its counties

Bonus: Which state has the highest average income? Which has the most variation within

its counties?

10.5 Try It Yourself (from the textbook)

Chapter 11 Exercises

1. Write a query to show the correlation between `pct_masters_higher` and `median_hh_income`. Is the r value higher or lower than bachelor's? What might explain the difference?
2. Create a **12-month rolling sum** using `soybeans_export_value`. Graph the results. What trend do you see?
3. **Bonus:** If you have the libraries data from Chapter 9 (`pls_fy2018_libraries`), rank library agencies by visits per 1,000 population for agencies serving 250,000+ people.

10.6 Further Reading

- **Practical SQL, 2nd Edition** — Chapter 11, by Anthony DeBarros
- PostgreSQL docs: Aggregate Functions
- PostgreSQL docs: Window Functions Tutorial
- PostgreSQL docs: Window Function List
- Fun: Spurious Correlations
- Deep dive: *Statistics* by Freedman, Pisani, and Purves

Happy querying! May your correlations be strong and your p-values be low.