

Computational & AI-Assisted Methods for Social Sciences

A Research Design Primer

Chapter 5

From Concepts to Measures

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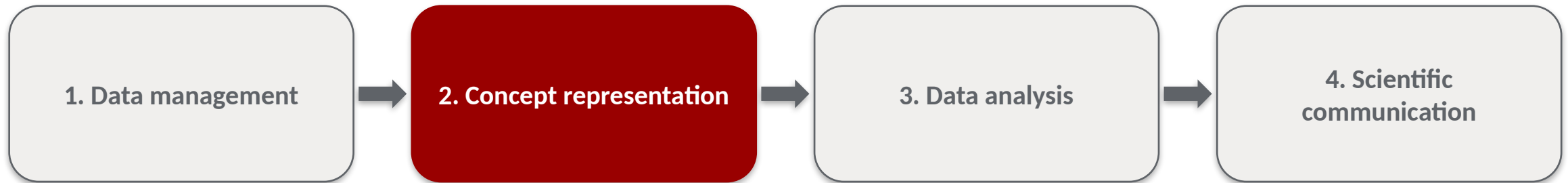
Learning objectives

By the end of this chapter, you can:

- Identify the four research worldviews and how each shapes computational measurement
- Distinguish deductive, inductive, and integrative approaches to concept representation
- Explain featurization and auxiliary instruments as bridges from raw data to theory
- Evaluate computational measures against conceptual-goodness, validity, and reliability criteria
- Diagnose the marginal-cases problem and its ethical stakes

Stage 2: concept representation

Chapter 5



Chapters 5 and 6 develop the second stage: turning abstract ideas into variables an analysis can use.

A measure is a chain of decisions, not a translation

- A dictionary, a topic model, and a network position can all claim to measure “influence”
- Each commits you differently, sees different cases, fails differently
- Failures are not evenly distributed; the missed cases are often the ones you most want
- “Representation”: measures are partial, theory-informed stand-ins for the concept

“In computational research, epistemology is not a preamble to the method; it is embedded in the method.”

Chapter 5

§5.1

Worldviews and purposes of social research



Four philosophical orientations, and the research goals each one serves.

Postpositivism: approximating an external reality

§5.1

- Cause-and-effect emphasis; reductionistic focus on a few key variables
- Objective reality approached through systematic observation and measurement
- Theory-driven cycle: propose, test, refine, repeat
- CSS example: classify millions of posts, model what drives virality

Constructivism: multiple realities, contextual meaning

§5.1

- Subjective, overlapping interpretations rather than a single truth
- Meaning emerges from historical, cultural, and social context
- Researcher reflexivity replaces claimed neutrality
- CSS example: topic-model a hashtag, then read, engage, and reflect

Transformative research: knowledge tied to social change

§5.1

- Centers marginalized groups; investigates power and inequity
- Action-oriented: findings feed advocacy, outreach, and policy proposals
- Participants co-design the research and share ownership
- CSS supports the work without leading it: networks map connections, topics surface demands

Pragmatism: what works, in context

§5.1

- Problem-centered inquiry; methodological freedom, mixed methods welcome
- The test of an idea: does it solve the concrete problem?
- CSS example on online bullying: NLP detection, network clusters, plus interviews

Worldviews map to computational measures

§5.1

	Postpositivism	Constructivism	Transformative	Pragmatism
Purpose	Test and refine theory; predict	Interpret phenomena; advance new theory	Explore diversity; give voice	Real-world practice oriented
Approach	Deductive measures	Inductive measures	Not bound to one approach	Not bound to one approach
Example method	Keyword-dictionary classification	Topic modeling	Social network analysis	New data source + ML classification
Example study	Golder & Macy (2011)	Hannigan et al. (2019)	Loutfi et al. (2020)	Asur & Huberman (2010)

§5.2

Epistemological approaches to computational measures



Deductive, inductive, and integrative routes from concept to code.

Deductive measures: categories defined before you look

§5.2

- Automated coding of raw data into predefined theoretical categories
- Word lists: “flowers” pleasant, “insects” unpleasant (Caliskan et al.)
- Machine learning extends the principle by learning from labeled examples
- Strengths: consistency and scalability on large datasets

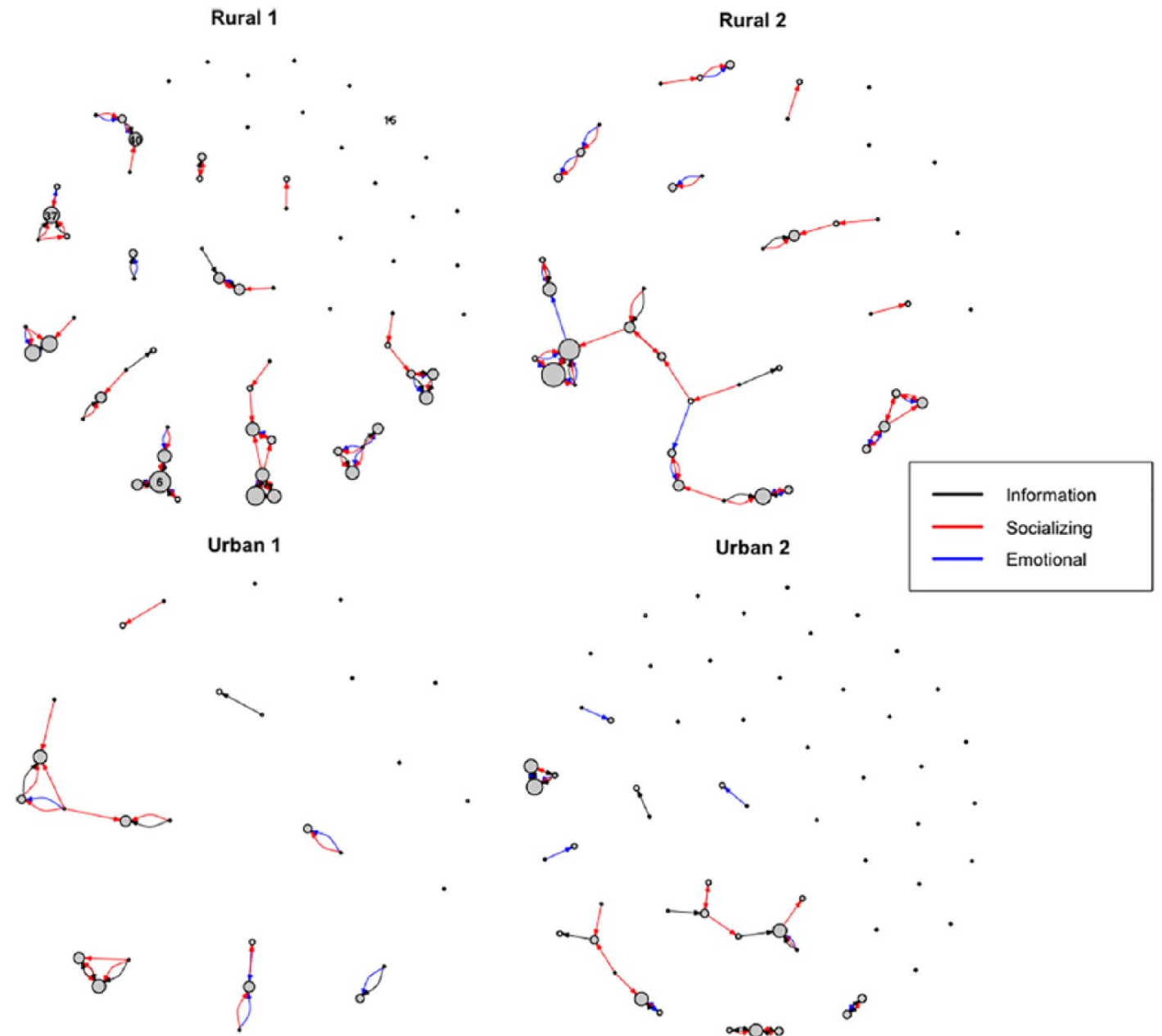
Inductive measures: letting structure emerge

§5.2

- A misconception: computational methods only serve postpositivist quantifiers
- The representational view: data represent the social world; insights emerge inductively
- Topic modeling within grounded theory, refined through manual reading
- Network analysis surfaces clusters and bridges you did not anticipate

Networks reveal how marginalized communities connect

Support networks of young women at high HIV risk in four Botswana communities. Node size: how often a participant was sought for support; tie color: information, socializing, or emotional support.



Source: Loutfi et al. (2020), Fig. 1, Global Health Promotion. © SAGE Publications. Included for instructional use.

Integrative measures and methodological bricolage

§5.2

- Start deductive (sentiment lexicon), then add inductive discovery (topic model)
- Keeps automated scalability while staying open to unanticipated patterns
- Bricolage: weaving multiple techniques into one workflow (Bonikowski)
- Abductive logic blurs the neat deduction-induction line

Method choice as three explicit decisions

§5.3

- Methods carry no fixed epistemology; your worldview supplies the link to the concept
- Decide the unit of analysis and data source
- Decide deductive, inductive, or integrative representation
- Decide which checks can support validity for this use

§5.4

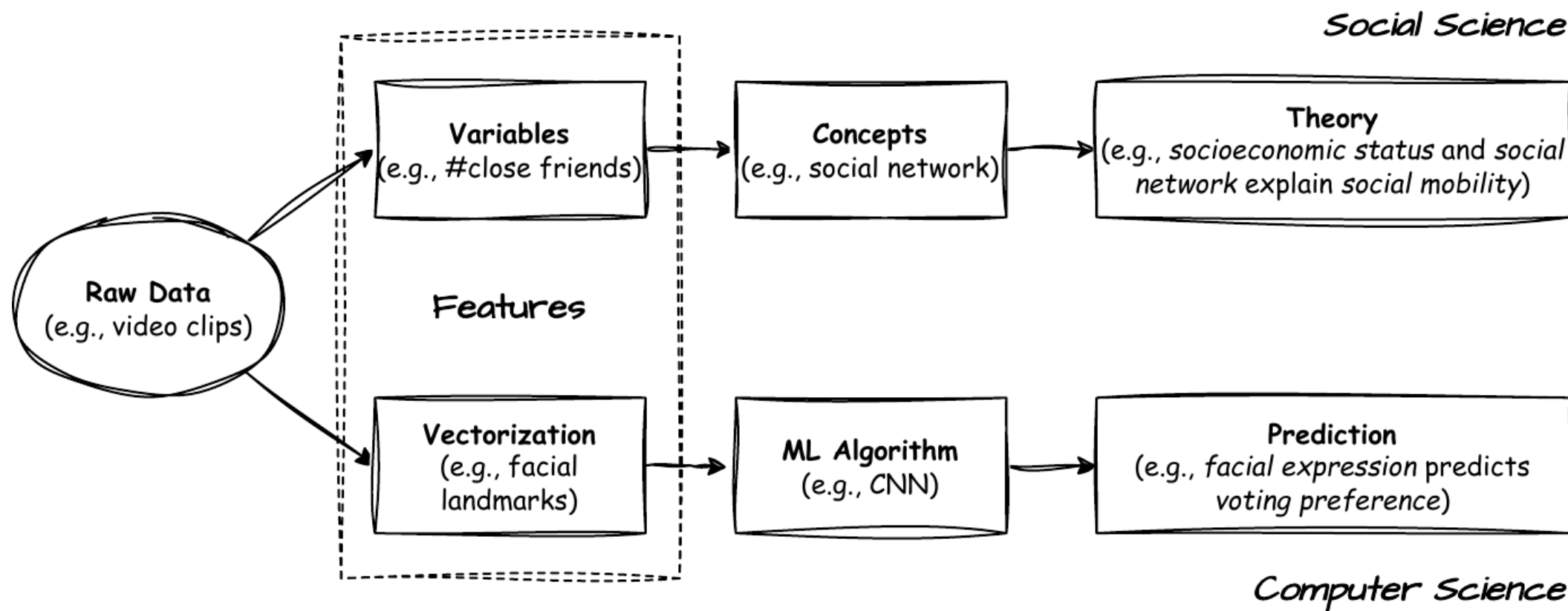
From raw data to socially meaningful variables



Featurization, and the auxiliary instruments that make measurement feasible.

Featurization sits between raw data and latent structure

§5.4



“Features” in social and computer sciences: observable variables cluster into concepts, and concepts become building blocks of theory.

➤ [Working with text data](https://cssprimer.org/primers/text-data) · cssprimer.org/primers/text-data

Same word “feature,” two disciplinary meanings

§5.4

Computer science

- Any measurable attribute: pixel intensity, word frequency
- Extracted automatically, purely data-driven
- Aim: maximize predictive performance

Social science

- A variable imbued with conceptual and theoretical meaning
- Chosen or coded to reflect theory: trust, social capital, framing
- Aim: preserve conceptual relevance

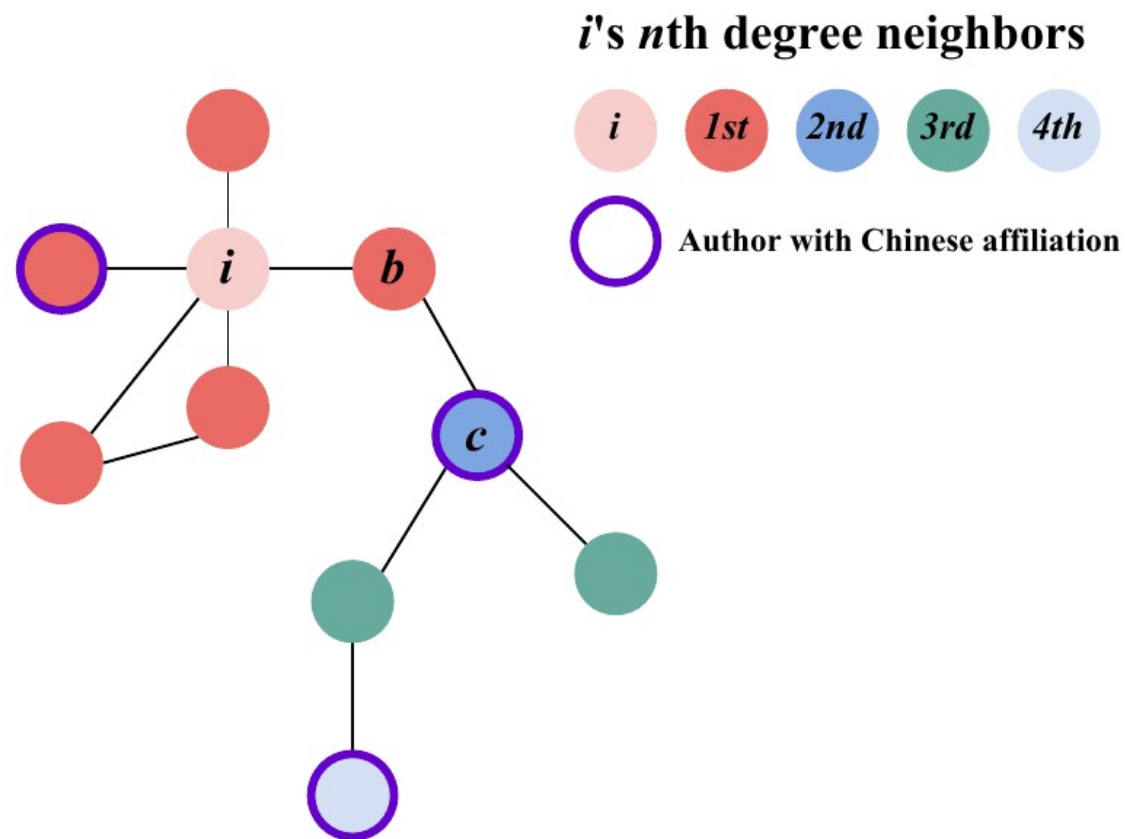
Auxiliary instruments: the bridge in the middle

§5.4

- Workflow: raw data → auxiliary instrument → measure (feature)
- “Instrument” means a practical measurement tool, not an instrumental variable
- Rarely the outcome of interest; it makes measurement feasible, reusable, transparent
- You can point to a concrete object: a network, a matrix

A coauthorship network measures closeness and connectedness

§5.4



Nodes are authors; an edge means at least one coauthored publication. Closeness becomes network distance (b is nearer to i than c); connectedness becomes degree (i has four ties, b has two). Adapted from Ma (2024), Fig. 1A.

The document-topic matrix turns topics into measures

§5.4

Entry: $\theta_{dk}, d=1, k=3$ Row: $\theta_d = (\theta_{d1}, \dots, \theta_{dK}), \sum_k \theta_{dk} = 1$

Doc 1	0.05	0.10	0.55	0.20	...
Doc 2	0.60	0.05	0.10	0.20	...
Doc 3	0.10	0.65	0.05	0.10	...
Doc 4	0.15	0.10	0.10	0.55	...
	Topic 1	Topic 2	Topic 3	Topic 4	

Topics ($k = 1, \dots, K$)

Rows are documents, columns are topics, entries are topic proportions summing to 1 per row. Recreated illustrative excerpt after Heiberger et al. (2021).

§5.5

What makes computational measures unique?



New data meets new analytical capacity — and new points of failure.

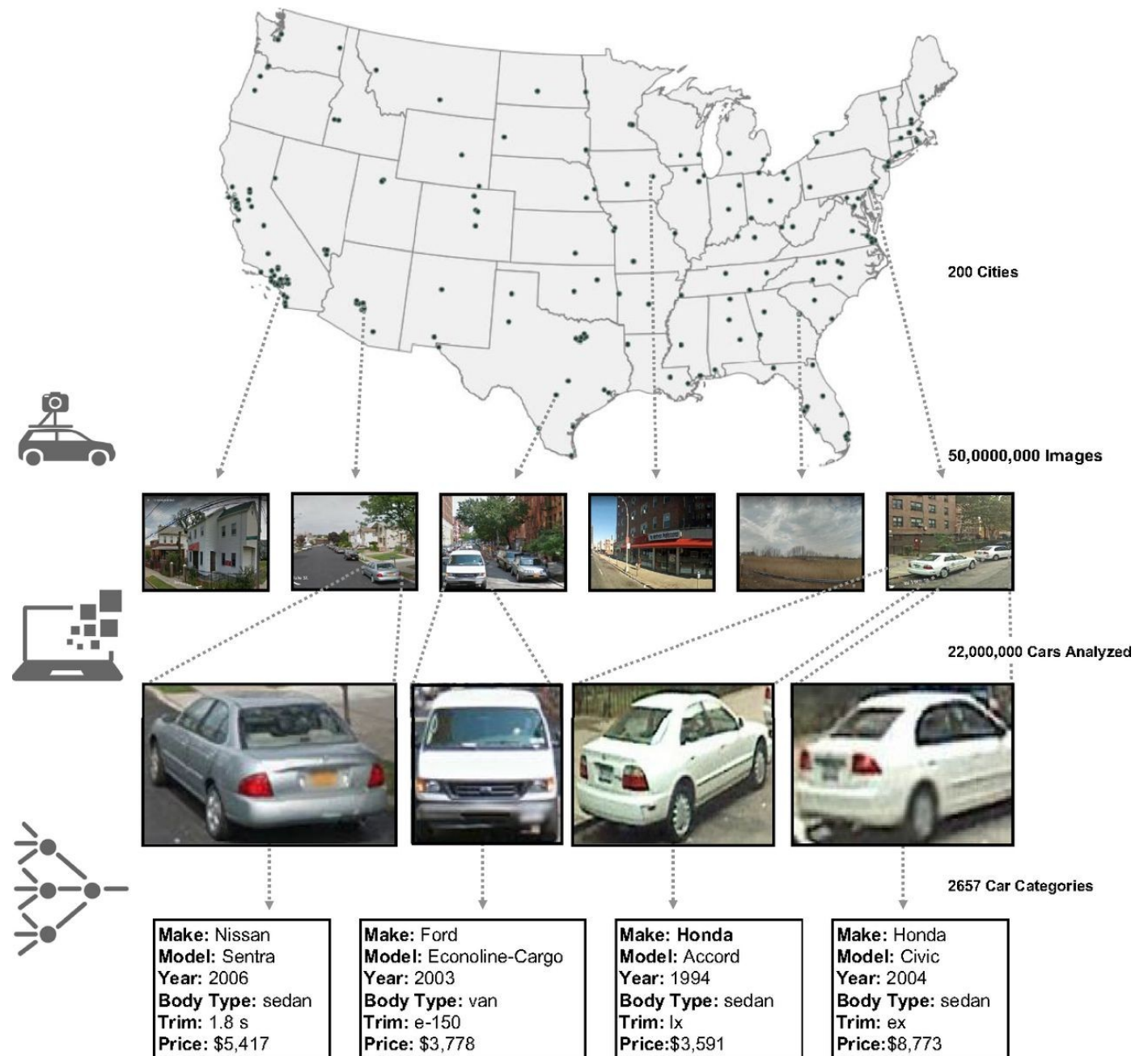
Found data: records produced for something else

§5.5

- Fine-grained, time-stamped behavioral traces at enormous scale
- Not simply more data: new kinds of data (who interacts with whom, when)
- Repurposing: reusing records collected for another purpose (Salganik)
- Risks: local conventions, shifting categories, undocumented provenance

Street View repurposed: cars predict demographics

50 million images across 200 U.S. cities; 22 million vehicles classified by make, model, and year. Aggregated vehicle features estimate income, race, education, and voting at ZIP-code and precinct level.



Source: Gebru et al. (2017), Fig. 1, PNAS. © National Academy of Sciences. Included for instructional use.

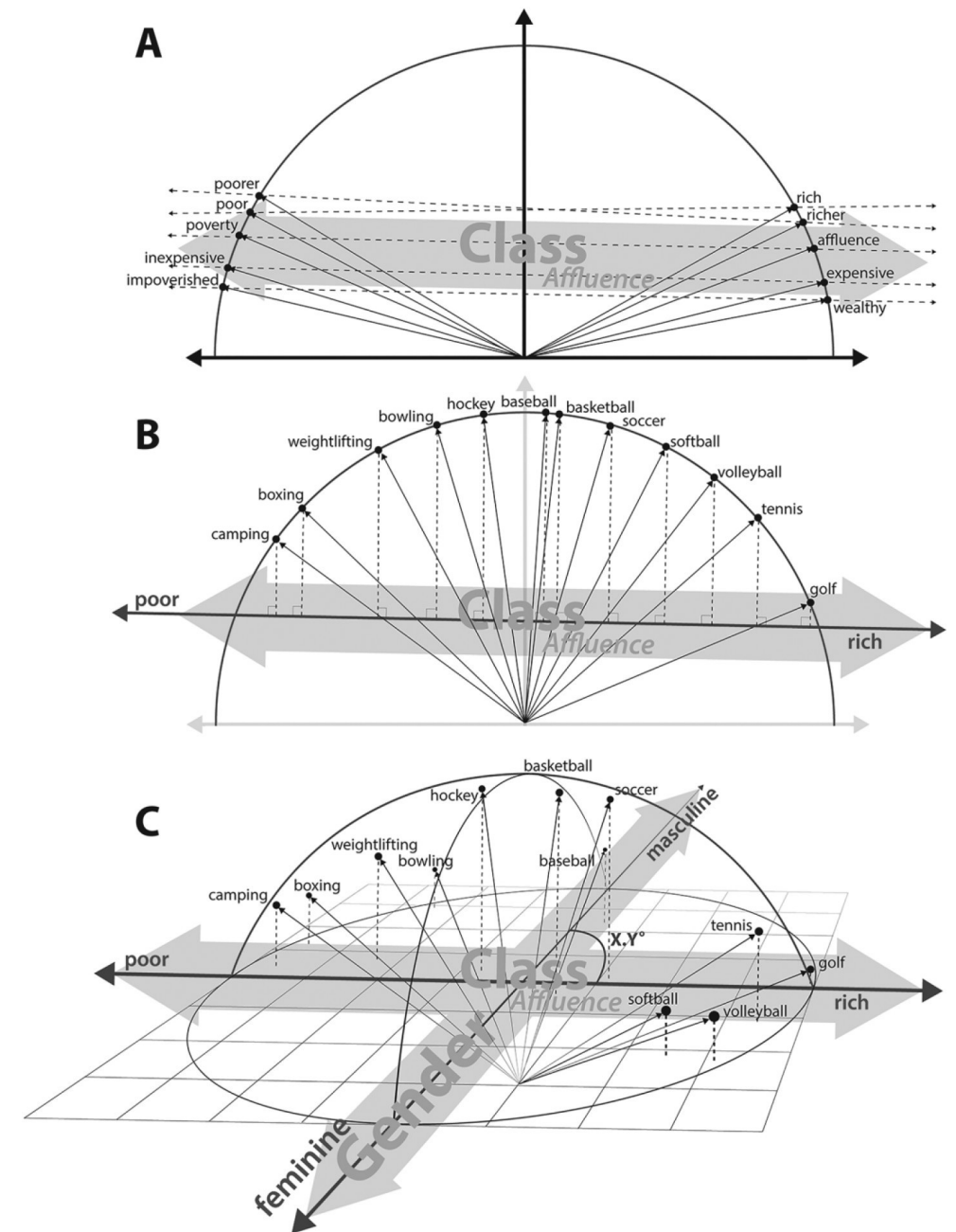
Analytical capacity, and its structural blind spot

§5.5

- Algorithms summarize high-dimensional records and amplify researcher coding
- Three forms this session: embeddings, transfer learning, generative measurement
- Abundant data teach majority patterns well and minority patterns poorly
- Social science often centers exactly those rare cases

Word embeddings as dimensions of cultural meaning

(A) Build an affluence dimension by averaging antonym pairs; (B) project words onto it — golf and tennis score affluent, boxing and camping poor; (C) angles between dimensions reveal how cultural axes entangle.



Source: Kozlowski et al. (2019), Fig. 2, American Sociological Review. © American Sociological Association. Included for instructional use.

Takeaway: Validation was uneven: correlation with surveys hit .53 for class, .76 for gender, only .27 for race.

Transfer learning and prompt-based measurement

§5.5

- Transfer learning: repurpose a pretrained model where labels are scarce (Laurer et al.)
- Transparency burden rises with pretraining you did not control
- Promptbook: prompts documented like a codebook (Stuhler et al.)
- Accuracy is field-specific: age 0.99, but religion quietly imputed

Traditional and computational measures capture different facets

§5.5

Concept	Traditional measures	Computational measures
Protest mobilization	Surveys, interviews, ethnography, event catalogs: who participated and what it meant	Follower and message networks from Twitter traces: how information spread, who amplified it (González-Bailón et al.)
Scientific consensus	Expert panels and systematic reviews interpreting evidence and arguments	Dynamic citation networks: declining modularity marks closure and consensus (Shwed & Bearman)

§5.6

Validity and reliability of “good concepts”



Eight criteria for the concept, six strategies for the measure.

Eight criteria of conceptual goodness (Gerring)

§5.6

Definition quality

- **Familiarity** — stay close to established usage
- **Resonance** — the label rings true to readers
- **Parsimony** — few defining attributes, no kitchen sinks
- **Coherence** — attributes hang together logically

Position among concepts

- **Differentiation** — influence must not be mere visibility
- **Depth** — scope conditions and facets specified
- **Theoretical utility** — instrument matches mechanism
- **Field utility** — leaves neighboring concepts their referents

Validity, reliability, and the evidence for each

§5.6

- Validity: does it capture what it claims? Reliability: is it stable?
- A measure can be reliable and consistently wrong
- Six strategies: face checks, benchmarks, outcome tests, theory tests, stability, error audits
- Multi-stage pipelines can introduce error at every stage

§5.7

The marginal-cases problem



Rare in the data, central to the theory.

Why algorithms struggle with rare but central cases

§5.7

- Protest events, equity framing, hate speech: small fractions of large corpora
- A 97% non-protest corpus teaches the majority pattern reliably, the minority poorly
- Topic models absorb rare themes; embeddings blur minority discourse
- Transfer learning helps with imbalance, but the asymmetry remains

Too small and too noisy: how the errors compound

§5.7

- False negatives remove genuine minority cases: suppression
- False positives add majority-class impostors: dilution
- Both distort the minority category in the same direction
- 97% aggregate accuracy is achievable while learning nothing about the minority class

“CSS expands what we can measure, but it does not relax the basic obligations of measurement.”

Chapter 5

AI as concept-development partner, not judge

§5.8

- Brainstorming: candidate concepts, dimensions, indicators — a hypothesis list, not evidence
- Mainstream by construction: suggestions tilt toward well-studied populations
- Adversarial review: ask the model to attack your operationalization
- AI cannot settle validity; fluent agreement is its easiest output

- Pick one concept from your research. How would a postpositivist represent it differently from a constructivist?
- Sketch a deductive and an inductive measure for that concept. What does each gain and lose?
- Would your project benefit from an auxiliary instrument, and which design choices would you need to justify?
- Which validation strategies are feasible for your project, and where are the largest threats?

Key concepts from Chapter 5

Concept representation: Translating abstract ideas into measurable variables; broader than operationalization

Research worldviews: Postpositivism, constructivism, transformative, pragmatism; each shapes measurement

Deductive measures: Predefined theoretical categories applied to data: dictionaries, supervised classifiers

Inductive measures: Patterns emerge from the data: topic modeling, network clustering

Integrative measures: Deductive and inductive combined; scalable yet open to emergent patterns

Featurization: Transforming raw data into socially meaningful variables

Auxiliary instrument: Intermediate representation — network, matrix, embedding — that makes a concept quantifiable

Conceptual goodness: Eight trade-off criteria, from familiarity to field utility (Gerring)

Validity and reliability: Capturing what is claimed vs. yielding stable results; multi-stage pipelines multiply both risks

Marginal-cases problem: Majority patterns learned well, rare but central cases distorted by false negatives and positives

Materials on the companion site

cssprimer.org

[Studies filtered to concept representation](https://cssprimer.org/ch05/) cssprimer.org/ch05/

The Practice assignment's pre-filtered slice of the studies browser

[Working with text data](https://cssprimer.org/primers/text-data) cssprimer.org/primers/text-data

The representation groundwork Chapter 6 assumes

[CSS Empirical Studies Database](https://cssprimer.org/studies/) cssprimer.org/studies/

The full database for comparisons across stages

Where to go next

- Read: Chapter 6, the automated-coding exercises that operationalize this chapter
- Practice: annotate two studies from the CSS Empirical Studies Database (worldview, measures, instruments, validity)
- Try: AI brainstorming and adversarial review on a concept from your own research