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Using Computational Thinking to Explore the Past, Present, and Future

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Every social studies teacher knows that our subject is somewhat like a TARDIS, the time machine *cum* spacecraft in *Doctor Who*.[1] The social studies curriculum travels through time and space, and, like the TARDIS, is bigger on the inside than it is on the outside. To an outsider, the social studies curriculum is a single line on a program of studies, 45 minutes of a student's school day. Those of us on the inside, however, know that our field covers history, geography, civics, economics, and much more; it prepares students for their *lifetime* as one among 7.5 billion sapient bipeds on this planet, and not just an end-of-course exam or a specific profession.

Unfortunately, conveying the TARDIS-like nature of social studies to outsiders is difficult, rather like explaining the operation of the TARDIS to someone who has never seen the television show *Doctor Who*. Outsiders may ask, why can't social studies be self-referential, like mathematics? Or contained within dualities, as with English / Language Arts? Or split off into distinct disciplines, similar to Biology, Chemistry, Physics, et al.? Even our students can fail to see how the myriad topics within and across the curriculum fold together in different ways.

One way to demonstrate and enact the limited-yet-unbounded nature of social studies is through *computational thinking*. Computational thinking is a set of problem-solving strategies that is intended, but not required, to take advantage of computers. The term was popularized in 2006 by Jeanette Wing and has become linked with twenty-first century skills and other forward-thinking frameworks; however, its history goes back to the flowering of computer science in the 1960s–80s.[2] Computational thinking includes several classic critical thinking skills, such as decomposition and abstraction, as well as elements that are more closely tied to computing, such as algorithm construction, recursion, and automation.

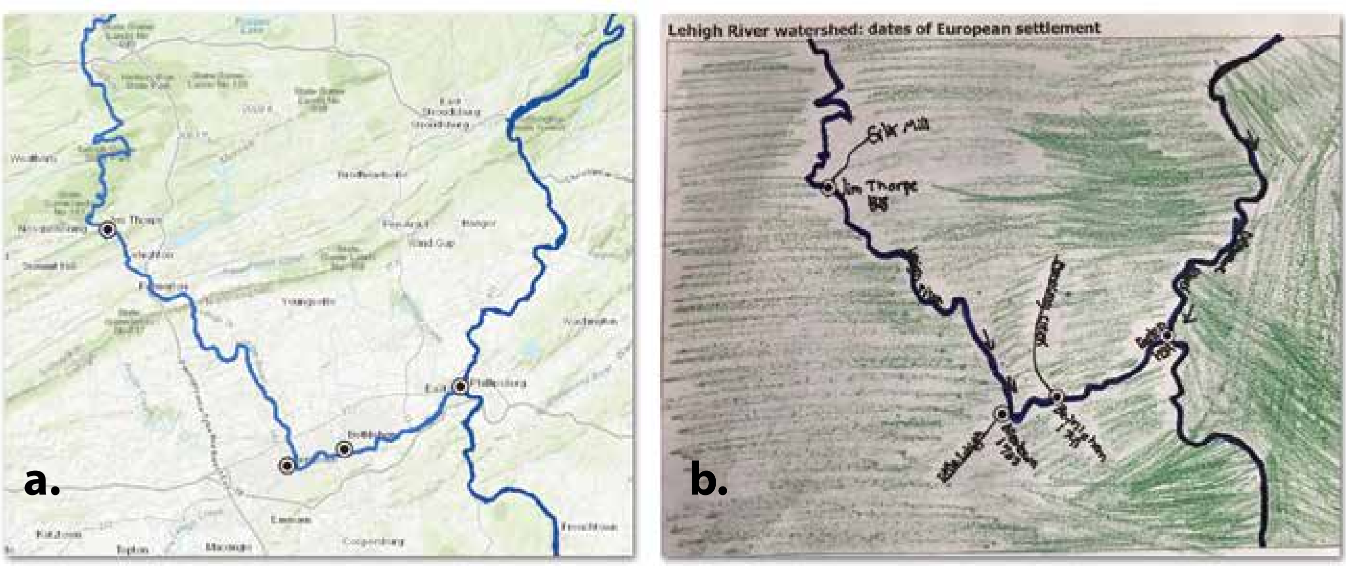


Figure 1: On the left, a map of the Lehigh Valley and selected historical settlements along it—available at https://arcg.is/0LiKD1. On the right, a student's annotated map showing the dates of settlement, direction of the river, and selected confluences.

Table 1. **Elements of Computational Thinking, Selected and Adapted for Social Studies Purposes**

Selected Elements of **Computational Thinking**[3]	**...Adapted and Explained for Social Studies**
• Symbol systems & representations • Abstractions & pattern generalizations • Algorithmic notions of flow control • Structured problem decomposition • Debugging & systematic error detection	Data definition: *What is being included? What is being excluded?* Pattern recognition & generalization: *What do I see? Does it apply elsewhere?* Abstraction: *Can I remove details to make it easier to see patterns or connections?* Rule-making: *Does a pattern always apply? Can it predict what will happen in a new situation?* Automation: *Can technology help me identify or confirm a pattern?* Decomposition: *Can I break this question or dataset into smaller parts?* Outlier analysis: *Which parts of the data do not follow the pattern? What can they tell us?*

The relevant elements of computational thinking are listed and explained in Table 1. However, we prefer to show rather than tell. Accordingly, we provide three examples of social studies instruction—across a variety of topic areas and grade levels—that incorporate computational thinking. Each of these examples, we hope, illustrates the value added by computational thinking, empowering social studies that is "bigger on the inside than it is on the outside."

Elementary Geography: Where are Settlements Located? Why?

Elementary social studies in our area of Pennsylvania covers local history and geography, focusing on the pre-colonial through colonial period of American history. A common topic is European settlements in the Lehigh Valley—when were they founded? Where? Who settled there? What peoples were already there, and how did the groups interact? As we look at the map (see Figure 1a on p.118), we immediately notice a pattern: the settlements are all next to a river. The teacher can next guide students through identifying two additional patterns (see Figure 1b, also on p. 118). First, the settlements are sequenced in time, and moving forward in time as they go further upstream. Second, the settlements all exist at confluences: Easton is at the junction of the Lehigh and Delaware Rivers; Bethlehem is where Monocacy Creek joins the Lehigh, and so on. Up to this point, the applicable elements of computational thinking are *abstraction* (as every map is an abstraction of the territory) and *pattern recognition* (observing the pattern of settlement expansion from downriver to upriver).

The more interesting stages come next: figuring out why these patterns exist and then extending them into *pattern generalization* and/or *rule-making*. The first step is orienting students to the time period: in eighteenth-century America, rivers and streams were the highways and roads. Establishing a settlement along the river was similar to building a house beside a road. Placing the settlement at a confluence of two or more waterways, then, was like setting up shop at a crossroads. Next, students can use the time data to infer that Europeans entered the Lehigh Valley from the confluence of the Lehigh and Delaware Rivers; from that point, Europeans spread upriver, founding new communities along the way. Can we generalize these patterns to other areas? What patterns exist for other time periods, in which other transit technologies ruled—for example, in the nineteenth century with the advent of canals and then railroads? Yes, towns sprang up along canals and at railroad junctions. By formulating a rule and seeing how it applies in different contexts (travel by water versus travel by rail), students use computational thinking to move forward and backward in time throughout the social studies curriculum. Teachers might even ask students to predict: where will the population shifts take place in the future? How might a changing climate influence these shifts? In all of these discussions, students will rely upon computational thinking skills—abstraction, decomposition, pattern recognition and generalization, and so forth—and also recognize that the topic at hand is larger and further-reaching than it first appears.

Middle Level U.S. History: What Do the Locations of Civil War Battles in the Eastern Theater Tell Us?

The Civil War is itself a TARDIS-like object, containing a veritable infinity of topics, interpretations, disputes, and more. Unfortunately, students rarely get a chance to appreciate this complexity, as teachers can bog down in the military narrative: a list of military leaders, a timeline of key battles and campaigns, and so on. Coincidentally, military history lends itself to computational thinking—it is already a *decomposition* (separating military operations from all other activities) and *abstraction* (focusing on battles rather than, say, supply chains or demographics). From this point, the teacher can engage the students in *pattern recognition*. Figure 2 (on p. 120) presents three different GIS displays of the Eastern Theater of the Civil War. The first image shows battle locations color-coded by campaign: Manassas, the Peninsula Campaign, Chancellorsville, Gettysburg, and so on. This map is meaningful and interesting to an expert, or perhaps a student focused on military history, but the presentation is not sufficiently abstracted to allow most students to engage in pattern recognition. The second map takes advantage of the *automation* within the GIS to re-code the battle sites by time: battles in 1861 or

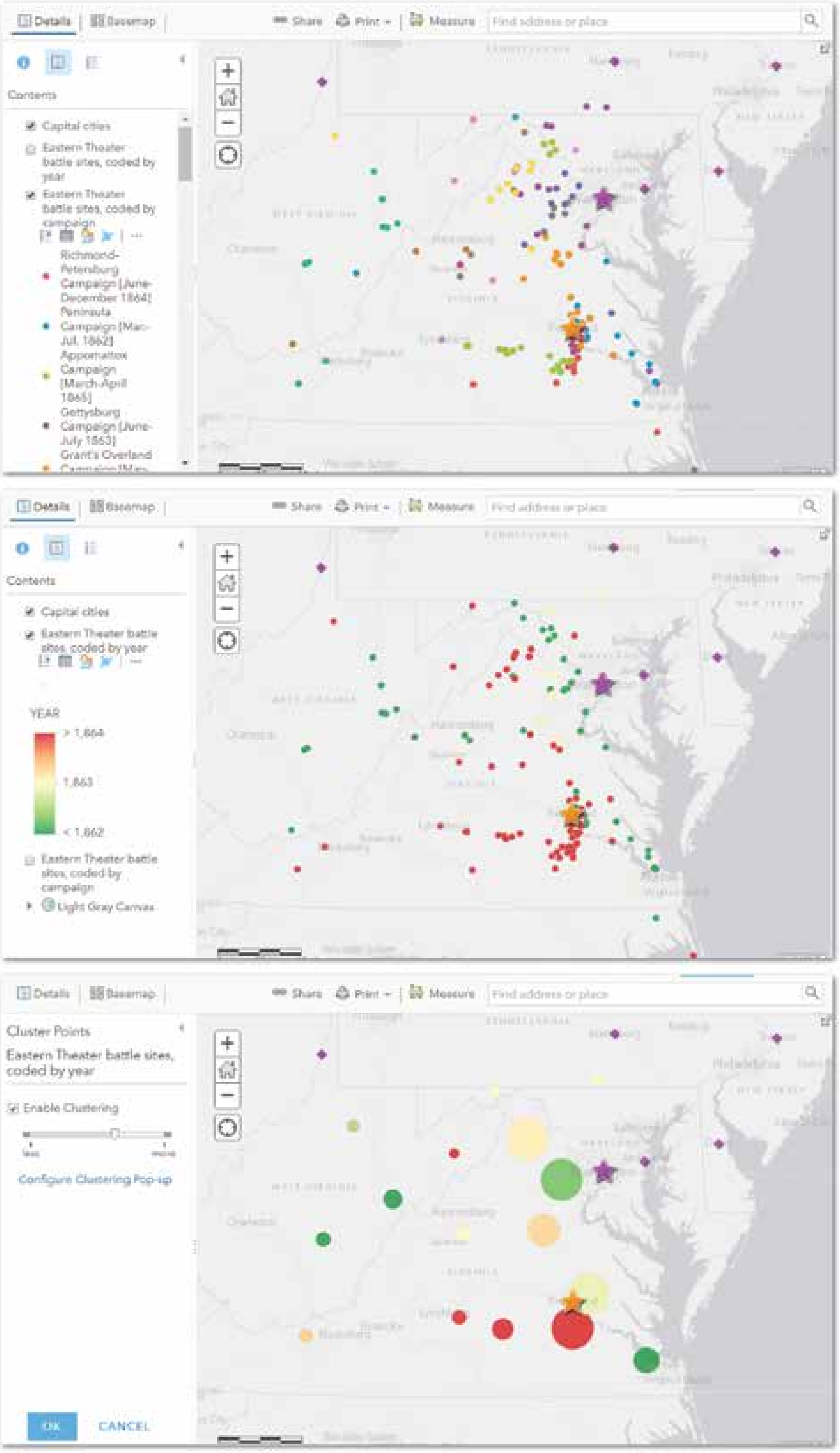


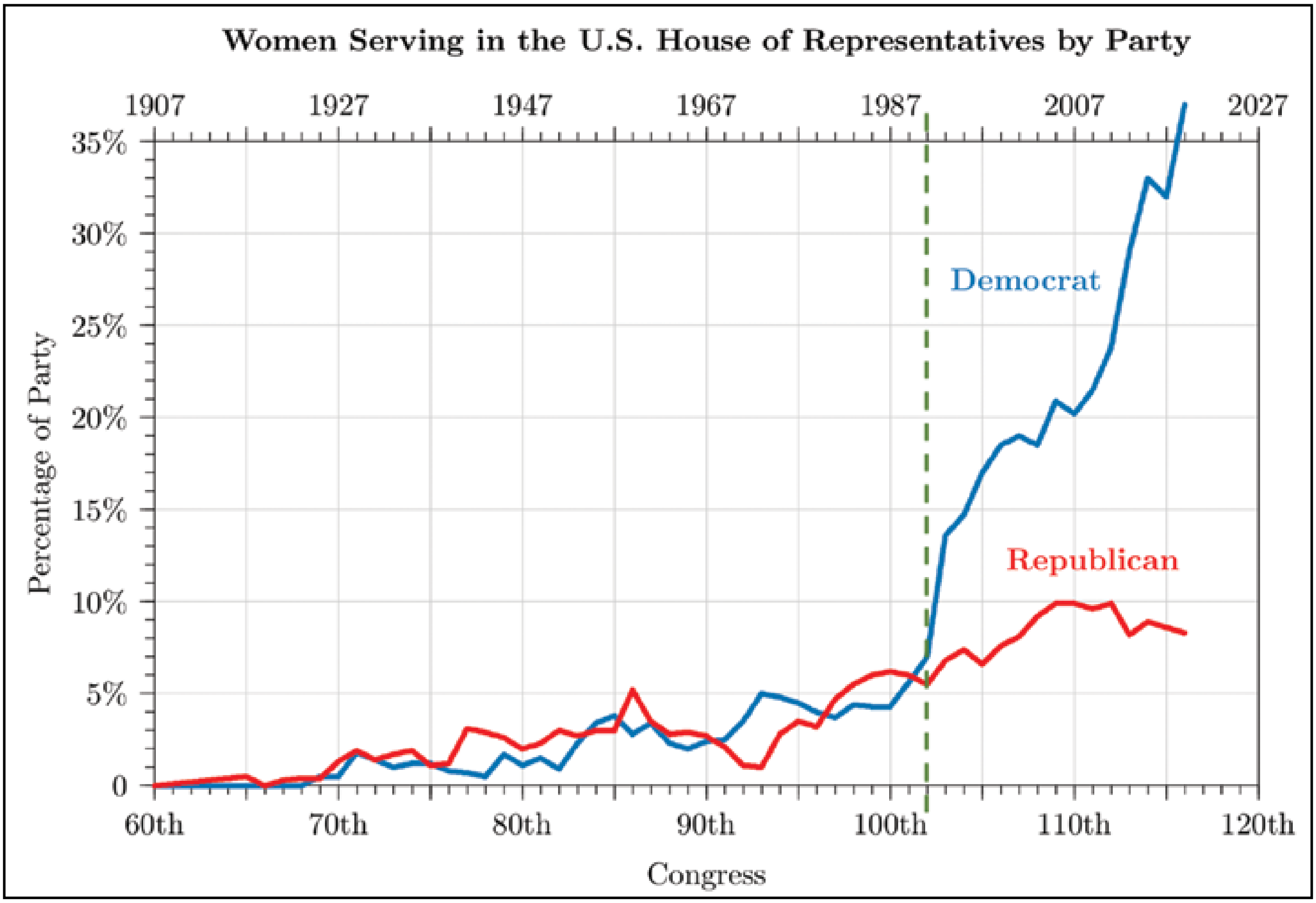
Figure 2: Three maps of the American Civil War battles in the Eastern Theater, available at https://arcg.is/0OqH8L. Top: battles color-coded by campaign. Middle: battles color-coded by year, plus capital cities. The large stars are Richmond and Washington, D.C. Bottom: The same map after a cluster analysis, condensing individual, color-coded dots into aggregate form.

1862 are green; battles in 1864 or 1865 are red. This greater level of abstraction simplifies the data and thus makes pattern recognition easier: the green dots (early battles) are largely on the perimeter of the theater, while the red dots (later battles) are generally contained within the green dots. This pattern suggests the broad strokes of the war in the Eastern Theater: the early phases established the boundaries of Union control (splitting West Virginia from Virginia, closing off the coastline, defending the Maryland border and Washington, D.C.), and the end of the war featured a long, grinding campaign to encircle the Confederate capital at Richmond. The third image shows even further abstraction, taking advantage of another feature of GIS: a cluster analysis, grouping the individual battle sites into larger dots that are still color-coded by year. This automated clustering allows students to confirm or disconfirm the previously observed pattern—are the green clusters at the perimeter? Are the red clusters all contained within the green clusters and focused on Richmond? For this topic, the application of computational thinking allows a teacher to shift a military *narrative* into an *analysis*.

Secondary Civics: What Patterns Exist in Women's Participation in Congress?

One indicator of a strong civics course is the way in which the curriculum addresses the increasingly important issue of political partisanship, particularly the demographic intersections of party affiliation. Partisan political demographers have been able to use GIS and computational thinking to conduct fine-grained analyses of demographics and partisanship to enable, among other things, the high-precision gerrymandering that created Republican majorities in state legislatures and congressional delegations since 2010.[5] One way to powerfully illustrate the importance of partisanship in a demographic context is to examine the number of women elected

Figure 3. **Women serving in the House of Representatives, divided by party, annotated to delineate two different trends by party.***



* Data adapted from Wikipedia, "Women in the United States House of Representatives" (San Francisco, Calif.: Wikimedia Foundation, 2018), https://en.wikipedia.org/wiki/Women_in_the_United_States_House_of_Representatives, with selection and additional analysis by authors.

to Congress. Wikipedia provides many fantastic datasets and visualizations, including a running tally of women in Congress. Figure 3 is one such data visualization, graphing women in the House of Representatives as a percentage of each major party delegation. The applicable computational thinking skills are *abstraction* (the graph) and *decomposition*—the graph shows only female representatives and splits them into parties. Furthermore, the graph can be divided into two contrasting stages. From 1907–1991, the two parties had very similar trends: small but growing numbers of women elected. From 1993 onwards we see different patterns across the parties: an increasing proportion of women in the Democratic caucus; flat or declining numbers of Republican women, never going above 10% of their caucus. Clearly, the two parties had a contrasting outcome from some inflection point that took place between 1991 and 1993: the testimony of Anita Hill during the confirmation hearings of Justice Clarence Thomas in 1991. A record-breaking 117 women won major-party nominations for the House or Senate in the following year's elections.[6]

To more clearly see the magnitude of the change, students can adapt the data tables in Wikipedia to analyze the percentage change in the number of women in Congress. Such a data table—see Table 2 for an example—takes advantage of the *automation* provided by spreadsheets and allows for more fine-grained *pattern recognition*. For example, we can observe three peaks in which the percentage increase of women in Congress neared or topped 20%: the 101st, the 103rd, and the 116th Congress. Can these similarly be linked to triggering events? And do these events similarly align women with the Democratic rather than the Republican party? If so, the students might engage in *rule-making*: the current gender gap in American partisan politics will persist barring a similar triggering event that might start prompting the election of more women in the Republican party.

Conclusion

Teaching about and with computational thinking is helpful in three ways. First, it provides a bridge between the C3 Framework's Dimension 2 (applying disciplinary concepts and tools) and

Dimension 3 (evaluating sources and using evidence). Computational thinking provides a toolset for analysis of discipline-specific data, and these tools stay consistent when shifting from history to civics to geography, and so on. Second, computational thinking can empower a more far-reaching, fluid approach to the social studies curriculum—the river becomes a timeline, the battlefields become an analytical narrative, and the demography of Congress becomes a lens into our political parties. Third, computational thinking may help social studies speak to the twenty-first century. We live in a data-rich age, and computational thinking will help students to investigate their own questions. As students become familiar with the techniques identified and demonstrated above, they will be able to think across time and space, using social studies to explore not only the past and present but the future as well. With any luck, they will leave your classroom bigger on the inside than when they entered.

Notes

1. The TARDIS ("Time And Relative Dimension In Space") is an object from the long-running television series *Doctor Who*. Effectively, the TARDIS is a time machine and spacecraft. Typical episodes begin with the Doctor emerging from the TARDIS, encountering and then resolving a problem, and finally re-entering the TARDIS, bound for a time and place.
2. Jeanette Wing, "Computational Thinking," *Communications of the ACM* 49 (2006): 33-35; Aman Yadav, Chris Mayfield, Ninger Zhou, Susanne Hambrusch, and John T. Korb, "Computational Thinking in Elementary and Secondary Teacher Education," *ACM Transactions on Computing Education* 14 (2014): 5.1–16; Peter J. Denning, "The Profession of IT: Beyond Computational Thinking," *Communications of the ACM* 52 (2009): 28–30.
3. Adapted from Shuchi Grover and Roy Pea, "Computational Thinking in K–12: A Review of the State of the Field," *Educational Researcher* 42 (2013): 38–43.
4. See The Redistricting Majority Project, "2012 REDMAP Summary Report" (Washington, D.C.: Republican State Leadership Committee, 2013), www.redistrictingmajorityproject.com/
5. Office of the Historian, "The Year of the Woman, 1992" (Washington, D.C.: United States House of Representatives, 2018), https://history.house.gov/Exhibitions-and-Publications/WIC/Historical-Essays/Assembling-Amplifying-Ascending/Women-Decade/
6. Figure source, with annotation by authors: Wikimedia Commons, "Women Serving in the U.S. House of Representatives by Party through 2019" (San Francisco, Calif.: Wikimedia Foundation, 2018), https://commons.wikimedia.org/wiki/File:Women_Serving_in_the_U.S._House_of_Representatives_by_Party_through_2019.png

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Table 2. **Women in the House and Senate During the 100th Through 116th Congresses**[8]

Congress	Years	Women in Congress	Change from previous year	Percentage change from previous year
100th	1987–1989	26		
101st	1989–1991	31	5	19.23%
102nd	1991–1993	33	2	6.45%
103rd	1993–1995	55	22	66.67%
104th	1995–1997	59	4	7.27%
105th	1997–1999	66	7	11.86%
106th	1999–2001	67	1	1.52%
107th	2001–2003	75	8	11.94%
108th	2003–2005	77	2	2.67%
109th	2005–2007	85	8	10.39%
110th	2007–2009	94	9	10.59%
111th	2009–2011	96	2	2.13%
112th	2011–2013	96	0	0.00%
113th	2013–2015	101	5	5.21%
114th	2015–2017	104	3	2.97%
115th	2017–2019	104	0	0.00%
116th	2019–2021	124	22	21.15%