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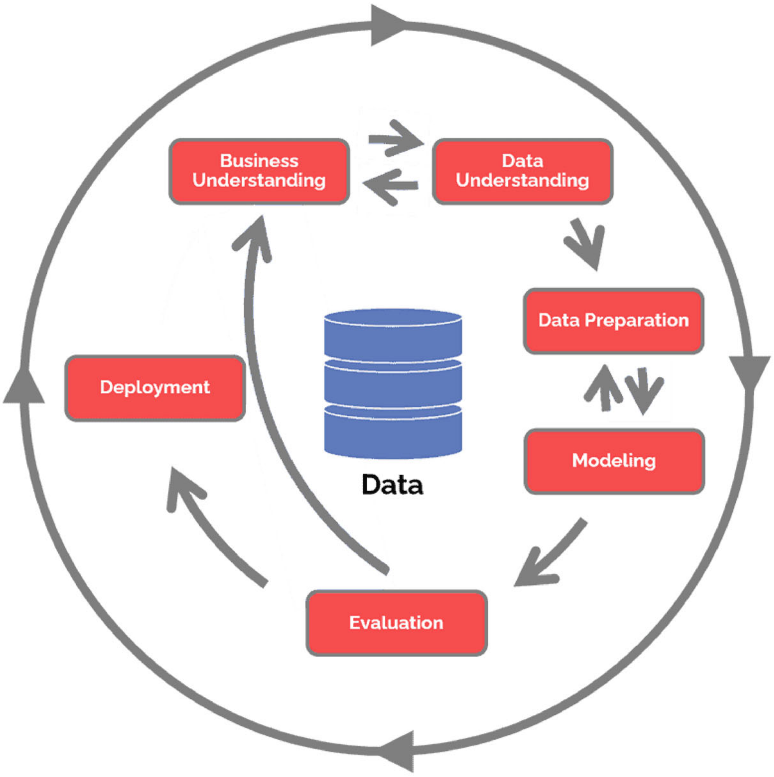
What is CRISP DM? - Data Science Process Alliance



CRISP-DM Diagram. Inspired by Wikipedia

The **CR**oss **I**ndustry **S**tandard **P**rocess for **D**ata **M**ining (*CRISP-DM*) is a process model that serves as the base for a data science process. It has six sequential phases:

1. Business understanding – What does the business need?
2. Data understanding – What data do we have / need? Is it clean?
3. Data preparation – How do we organize the data for modeling?
4. Modeling – What modeling techniques should we apply?
5. Evaluation – Which model best meets the business objectives?
6. Deployment – How do stakeholders access the results?

Published in 1999 to standardize data mining processes across industries, it has since become the most common methodology for data mining, analytics, and data science projects.

Data science teams that combine a loose implementation of CRISP-DM with overarching team-based agile project management approaches will likely see the best results.

CRISP-DM Training & Certification

Master the skills and gain the confidence to deliver data science projects and to lead data teams. Grow by earning the Data Science Team Lead certification. Available in individual courses and in private group courses.

What are the 6 CRISP-DM Phases?

I. Business Understanding

Any good project starts with a deep understanding of the customer's needs. Data mining projects are no exception and CRISP-DM recognizes this.

The *Business Understanding* phase focuses on understanding the objectives and requirements of the project. Aside from the third task, the three other tasks in this phase are foundational project management activities that are universal to most projects:

1. **Determine business objectives:** You should first "thoroughly understand, from a business perspective, what the customer really wants to accomplish." (CRISP-DM Guide) and then define business success criteria.
2. **Assess situation:** Determine resources availability, project requirements, assess risks and contingencies, and conduct a cost-benefit analysis.
3. **Determine data mining goals:** In addition to defining the business objectives, you should also define what success looks like from a technical data mining perspective.
4. **Produce project plan:** Select technologies and tools and define detailed plans for each project phase.

While many teams hurry through this phase, establishing a strong business understanding is like building the foundation of a house – absolutely essential.

II. Data Understanding

Next is the *Data Understanding* phase. Adding to the foundation of *Business Understanding*, it drives the focus to identify, collect, and analyze the data sets that can help you accomplish the project goals. This phase also has four tasks:

1. **Collect initial data:** Acquire the necessary data and (if necessary) load it into your analysis tool.
2. **Describe data:** Examine the data and document its surface properties like data format, number of records, or field identities.
3. **Explore data:** Dig deeper into the data. Query it, visualize it, and identify relationships among the data.
4. **Verify data quality:** How clean/dirty is the data? Document any quality issues.

III. Data Preparation

A common rule of thumb is that 80% of the project is data preparation.

This phase, which is often referred to as “data munging”, prepares the final data set(s) for modeling. It has five tasks:

1. Select data: Determine which data sets will be used and document reasons for inclusion/exclusion.
2. Clean data: Often this is the lengthiest task. Without it, you’ll likely fall victim to garbage-in, garbage-out. A common practice during this task is to correct, impute, or remove erroneous values.
3. Construct data: Derive new attributes that will be helpful. For example, derive someone’s body mass index from height and weight fields.
4. Integrate data: Create new data sets by combining data from multiple sources.
5. Format data: Re-format data as necessary. For example, you might convert string values that store numbers to numeric values so that you can perform mathematical operations.

IV. Modeling

What is widely regarded as data science's most exciting work is also often the shortest phase of the project.

Here you'll likely build and assess various models based on several different modeling techniques. This phase has four tasks:

1. Select modeling techniques: Determine which algorithms to try (e.g. regression, neural net).
2. Generate test design: Pending your modeling approach, you might need to split the data into training, test, and validation sets.
3. Build model: As glamorous as this might sound, this might just be executing a few lines of code like "reg = LinearRegression().fit(X, y)".
4. Assess model: Generally, multiple models are competing against each other, and the data scientist needs to interpret the model results based on domain knowledge, the pre-defined success criteria, and the test design.

Although the CRISP-DM Guide suggests to "iterate model building and assessment until you strongly believe that you have found the best model(s)", in practice teams should continue iterating until they find a "good enough" model, proceed through the CRISP-DM lifecycle, then further improve the model in future iterations.

V. Evaluation

Whereas the A*ssess Model* task of the *Modeling* phase focuses on technical model assessment, the *Evaluation* phase looks more broadly at which model best meets the business and what to do next. This phase has three tasks:

1. Evaluate results: Do the models meet the business success criteria? Which one(s) should we approve for the business?
2. Review process: Review the work accomplished. Was anything overlooked? Were all steps properly executed? Summarize findings and correct anything if needed.
3. Determine next steps: Based on the previous three tasks, determine whether to proceed to deployment, iterate further, or initiate new projects.

VI. Deployment

"Depending on the requirements, the deployment phase can be as simple as generating a report or as complex as implementing a repeatable data mining process across the enterprise."

A model is not particularly useful unless the customer can access its results. The complexity of this phase varies widely. This final phase has four tasks:

1. Plan deployment: Develop and document a plan for deploying the model.
2. Plan monitoring and maintenance: Develop a thorough monitoring and maintenance plan to avoid issues during the operational phase (or post-project phase) of a model.
3. Produce final report: The project team documents a summary of the project which might include a final presentation of data mining results.
4. Review project: Conduct a project retrospective about what went well, what could have been better, and how to improve in the future.

Your organization's work might not end there. As a project framework, CRISP-DM does not outline what to do after the project (also known as "operations"). But if the model is going to production, be sure you maintain the model in production. Constant monitoring and occasional model tuning is often required.

Is CRISP-DM Agile or Waterfall?

Some argue that it is flexible and agile and while others see CRISP-DM as rigid. What really matters is how you implement it.

Waterfall: On one hand, many view CRISP-DM as a rigid waterfall process – in part because of its reporting requirements that are excessive for most projects. Moreover, the guide states in the business understanding phase that "the project plan contains detailed plans for each phase" – a hallmark aspect of traditional waterfall approaches that require detailed, upfront planning.

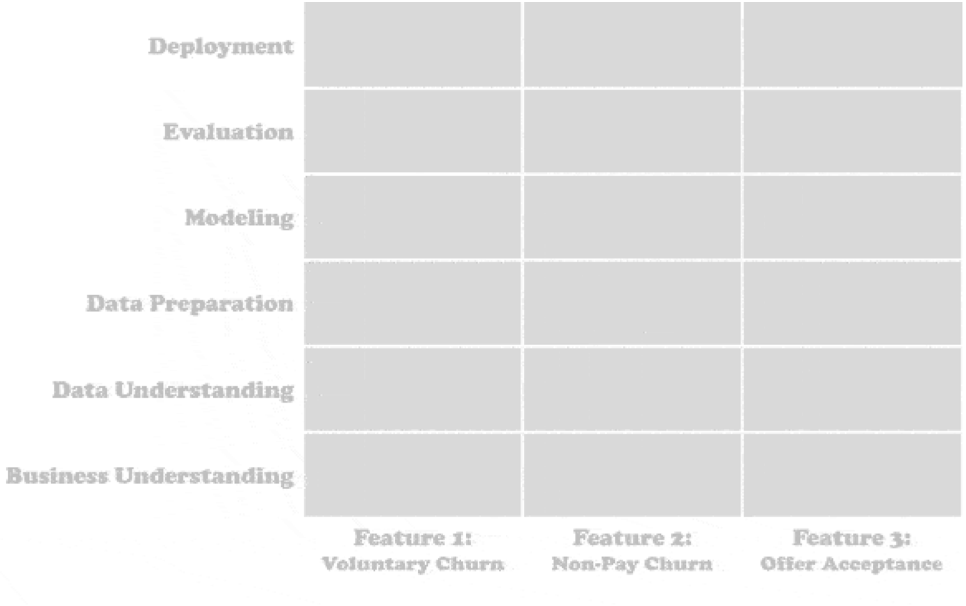
Indeed, if you follow CRISP-DM precisely (defining detailed plans for each phase at the project start and include every report) and choose not to iterate frequently, then you're operating more of a waterfall process.

Agile: On the other hand, CRISP-DM indirectly advocates agile principles and practices by stating: "The sequence of the phases is not rigid. Moving back and forth between different phases is always required. The outcome of each phase determines which phase, or particular task of a phase, has to be performed next."

Thus if you follow CRISP-DM in a more flexible way, iterate quickly, and layer in other agile processes, you'll wind up with an agile approach.

Example: To illustrate how CRISP-DM could be implemented in either an Agile or waterfall manner, imagine a churn project with three deliverables: a voluntary churn model, a non-pay disconnect churn model, and a propensity to accept a retention-focused offer.

In a waterfall-style implementation, the team's work would comprehensively and horizontally span across each deliverable as shown below. The team might infrequently loop back to a lower horizontal layer only if critically needed. One "big bang" deliverable is delivered at the end of the project.



CRISP-DM Agile: Vertical Slicing

Alternatively, in an agile implementation of CRISP-DM, the team would narrowly focus on quickly delivering one vertical slice up the value chain at a time as shown below. They would deliver multiple smaller vertical releases and frequently solicit feedback along the way.

Which is better?

When possible, take an agile approach and slice vertically so that:

- Stakeholders get value sooner
- Stakeholders can provide meaningful feedback
- The data scientists can assess model performance earlier
- The project team can adjust the plan based on stakeholder feedback

How popular is CRISP-DM?

Definitive research does not exist on how frequently data science teams use different management approaches. So to get an idea on approach popularity, we investigated KDnuggets polls, conducted our own poll, and researched Google search volumes. Each of these views suggests that **CRISP-DM is the most commonly used approach** for data science projects.

KDnuggets Polls

Bear in mind that the website caters toward data mining, and the data science field has changed a lot since 2014.

KDnuggets is a common source for data mining methodology usage. Each of the polls in 2002, 2004, 2007 posed the question: “What main methodology are you using for data mining?”, and the 2014 poll expanded the question to include “…for analytics, data mining, or data science projects.” 150-200 respondents answered each poll.

CRISP-DM was the popular methodology in each poll spanning the 12 years.

Our 2020 Poll

To learn more about the poll, go to this post.

For a more current look into the popularity of various approaches, we conducted our own poll on this site in August and September 2020.

Note the response options for our poll were different from the KDnuggets polls and our site attracts a different audience.

CRISP-DM was the clear winner, garnering nearly half of the 109 votes.

Google Searches

Given the ambiguity of a searcher's intent, some searches like “my own” could not be analyzed and others like “tdsp” and “semma” could be misleading.

For yet third view into CRISP-DM, we turned to Google Keyword Planner tool which provided the average monthly search volumes in the USA for select key search terms and related terms (e.g. “crispdm” or “crisp dm data science”). Clearly irrelevant searches like “tdsp electrical charges” or “semma both aagatha” were then removed.

CRISP-DM yet again reigned as king, and this time with a much broader margin.

Should I use CRISP-DM for Data Science?

So CRISP is popular. But **should you use it?**

Like most answers in data science, it's kind of complicated. But here's a quick overview.

Benefits

From today's data science perspective this seems like common sense. This is exactly the point. The common process is so logical that it has become embedded into all our education, training, and practice.

-William Vorheis, one of CRISP-DM's authors (from Data Science Central)

- **Generalize-able:** Although designed for data mining, William Vorhies, one of the creators of CRISP-DM, argues that because all data science projects start with business understanding, have data that must be gathered and cleaned, and apply data science algorithms, "CRISP-DM provides strong guidance for even the most advanced of today's data science activities" (Vorhies, 2016).
- **Common Sense:** When students were asked to do a data science project without project management direction, they "tended toward a CRISP-like methodology and identified the phases and did several iterations." Moreover, teams which were trained and explicitly told to implement CRISP-DM performed better than teams using other approaches (Saltz, Shamshurin, & Crowston, 2017).
- **Adopt-able:** Like Kanban, CRISP-DM can be implemented without much training, organizational role changes, or controversy.
- **Right Start:** The initial focus on *Business Understanding* is helpful to align technical work with business needs and to steer data scientists away from jumping into a problem without properly understanding business objectives.

- **Strong Finish:** Its final step *Deployment* likewise addresses important considerations to close out the project and transition to maintenance and operations.
- **Flexible:** A loose CRISP-DM implementation can be flexible to provide many of the benefits of agile principles and practices. By accepting that a project starts with significant unknowns, the user can cycle through steps, each time gaining a deeper understanding of the data and the problem. The empirical knowledge learned from previous cycles can then feed into the following cycles.

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Weaknesses & Challenges

In a controlled experiment, students who used CRISP-DM “were the last to start coding” and “did not fully understand the coding challenges they were going to face”

Dive Deeper: Explore key actions to consider

for Data Science projects using CRISP-DM

Get our White Paper

What are other CRISP-DM Alternatives?

See the main article for SEMMA

See the main article for KDD and Data Mining Process

SEMMA

A few years prior to the publication of CRISP-DM, SAS independently developed *Sample, Explore, Modify, Model, and Assess (SEMMA)*. Although designed to help guide users through tools in SAS Enterprise Miner for data mining problems, SEMMA is often considered to be a general data mining methodology (Tiwari & Dixit, 2017). SEMMA (8.5%) was the third most popular methodology per the 2014 KDnuggets poll, but its use is down from 13% in 2007.

Compared to CRISP-DM, SEMMA is even more narrowly focused on the technical steps of data mining. It skips over the initial *Business Understanding* phase from CRISP-DM and instead starts with data sampling processes. SEMMA likewise does not cover the final *Deployment* aspects. Otherwise, its phases somewhat mirror the middle four phases of CRISP-DM. Although potentially useful as a process to follow data mining steps, SEMMA should not be viewed as a comprehensive project management approach.

KDD and KDDS

Knowledge Discovery in Database (KDD) is the general process of discovering knowledge in data through *data mining,* or the extraction of patterns and information from large datasets using machine learning, statistics, and database systems.

In 2016, Nancy Grady of SAIC, expanded upon CRISP-DM to publish the *Knowledge Discovery in Data Science (KDDS).* "As an end-to-end process model from mission needs planning to the delivery of value", KDDS specifically expands upon CRISP-DM to address big data problems. It also provides some additional integration with management processes. KDDS defines four distinct phases: a*ssess, architect, build,* and *improve* and five process stages: *plan, collect, curate, analyze,* and *act* (Grady, 2016*).*

KDDS can be a useful expansion of CRISP-DM for big data teams. However, KDDS only addresses some of the shortcomings of CRISP-DM. For example, it is not clear how a team should iterate when using KDDS. In addition, its combination of phases and processes is less straight-forward. Adoption of KDDS outside of SAIC is not known.