PacificCPE

COURSE

60452A

Foundations for AI and Audit: Part 2

Machine learning is no longer a concept reserved for data scientists—it's becoming a practical tool for audit professionals. This course breaks down how machine learning works, why it's gaining traction in accounting, and how firms can begin building an intelligent, AI-assisted audit practice. You'll explore the planning toolkit needed to structure an AI-augmented audit firm, giving you a concrete foundation for moving from curiosity to implementation. Ideal for practitioners ready to take their first real steps toward smarter, technology-driven auditing.

CREDIT HOURS 2 | FIELD OF STUDY BUSINESS | EXAM QUESTIONS 10

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LEARNING ASSIGNMENTS AND OBJECTIVES

Assignment

- Study the full course materials included here.
- Complete the review questions after each chapter.
- Answer 10 final exam questions.
- Final exam is scored immediately, 70% or better passes.
- Certificate of completion is available in your account.
- Failed exams can be retaken free of charge.

Course Objectives

- Identify machine learning concepts.
- Recall the various methods of supervised and unsupervised machine learning.
- Recall the degrees of planning created by the American Institute of Artificial Intelligence.

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Publication Date: May 2026

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Chapter 1: RISE OF MACHINE LEARNING

Chapter Objective

After completing this chapter, you should be able to:

- Identify machine learning concepts.

Accountants understand and speak the language of business. Becoming an accountant is not a trivial undertaking. Through their training and education, they acquire the ability to abstract all the activities of a business to a higher dimension and then provide a measure of the business's performance at any given time. That ability to abstract and translate business activities into accounting frameworks requires years of sophisticated training. One has to understand the business context, observe the activity, determine if it is accounting worthy, abstract the key features of the transaction, cull out the recordable elements, and then record the transaction in the right buckets. The cognitive tasks of doing these steps are complex. Yet, experts are forecasting that most, if not all, of the accounting process will be automated. Many projects are underway to do just that. The optimism about the ability to achieve that automation is driven by the recent developments in machine learning. As previously stated, machine learning is a branch of artificial intelligence.

POWER OF PATTERNS

Point to a toy car and ask a child what is it that you are pointing to and it is likely that the child will respond "a car." The child never sat in the toy car. She never went in that car for a drive. But she calls it a car anyway. In her mind the toy car carries some properties of a real car and therefore it is a car.

Nature's strategy for achieving complexity from simplicity is evident in both the physical and cognitive constructs of our world. Human learning is no different. While the apparatus used for learning in humans is composed of 2.5 pounds of matter that we call brain, this organ can create colossally impressive work products, emotions, strategies, and survival mechanisms.

At the root of all cognitive learning and functions are some basic mechanisms at work. For example, the ability to identify things, that is, to know the difference between a chair and a table, a car and a truck, a human and an ape. This ability to identify things goes beyond being able to name things. For instance, when we scan a bar code, the

computer returns the name of the product. But humans do not need any bar codes to name products. When we see one, we know it is a car or a truck or a bus. When we hear the word “car,” it brings to mind an understanding what that word means. We even assign properties such as “new car smell” to a car and can determine if we are in a car simply by smell or the tactile feeling by touch.

The meaning comes from our knowledge of what a car does, what it looks like, feels like, its function and other such things. It is as if we have templates in our minds that say if certain properties add up, then it must be a car. The specific configuration of those properties is what we can call a pattern. Thus, pattern can be viewed as an expression of a certain assembly of properties with some values. In some ways, we can view our world – that is, all the things we can name – as pattern configurations.

Humans are good at identifying patterns. For instance, when we use the word “car” and we are given two very different looking cars, for example, a Mini and a Mercedes, we are able to determine that both are cars. This means that our ability to name a car as a car is not specific to a particular instance of a car, but instead it is a general concept of what a car is. This means that our templates are not rigid. They are somewhat generalizable. It also means that when we assign meaning via pattern configurations, we do that in a class membership fashion. In other words, we can define a class based upon some properties and the class can have members – and we can form subclasses based upon different values of the properties. But every one of those classes are expressions of patterns with some properties and values of those properties. For example, Automobiles > Cars > Mercedes, each can be thought of as a class with some properties that generalize over some values.

Based on the above discussion, we can see that our pattern recognition falls under at least two concept categories. The first is about understanding general categories, that is, abstracting something to a level where we understand that members of that class represent a pattern (e.g., four wheels, steering wheel, seats belong to the class car) of some type.

Second, pattern recognition is being able to read the tealeaves. This means to get some related data about something and then based upon that being able to project. We do that intuitively by knowing the relationships between things. The pattern configurations are not limited to objects or things. They can also represent relationships between things. For example, when we see clouds forming, we can anticipate that rain is coming. In this example, both cloud and rain can be viewed as pattern configurations – each with their respective properties. When combined, they also possess a relationship pattern where we can observe that the presence of one can lead to the other. In some ways, we can view that the cloud-forming was a property of

rain. We can add other factors to that as well. Other pattern elements could be temperature, wind, moisture, and so on. But how do we know what is temperature as a concept, what is wind, what is cloud formation, what is moisture? Well, we can use the same strategy, that is, to understand each of them by their properties. Clouds have a visual look – dark clouds, high clouds, and so on.

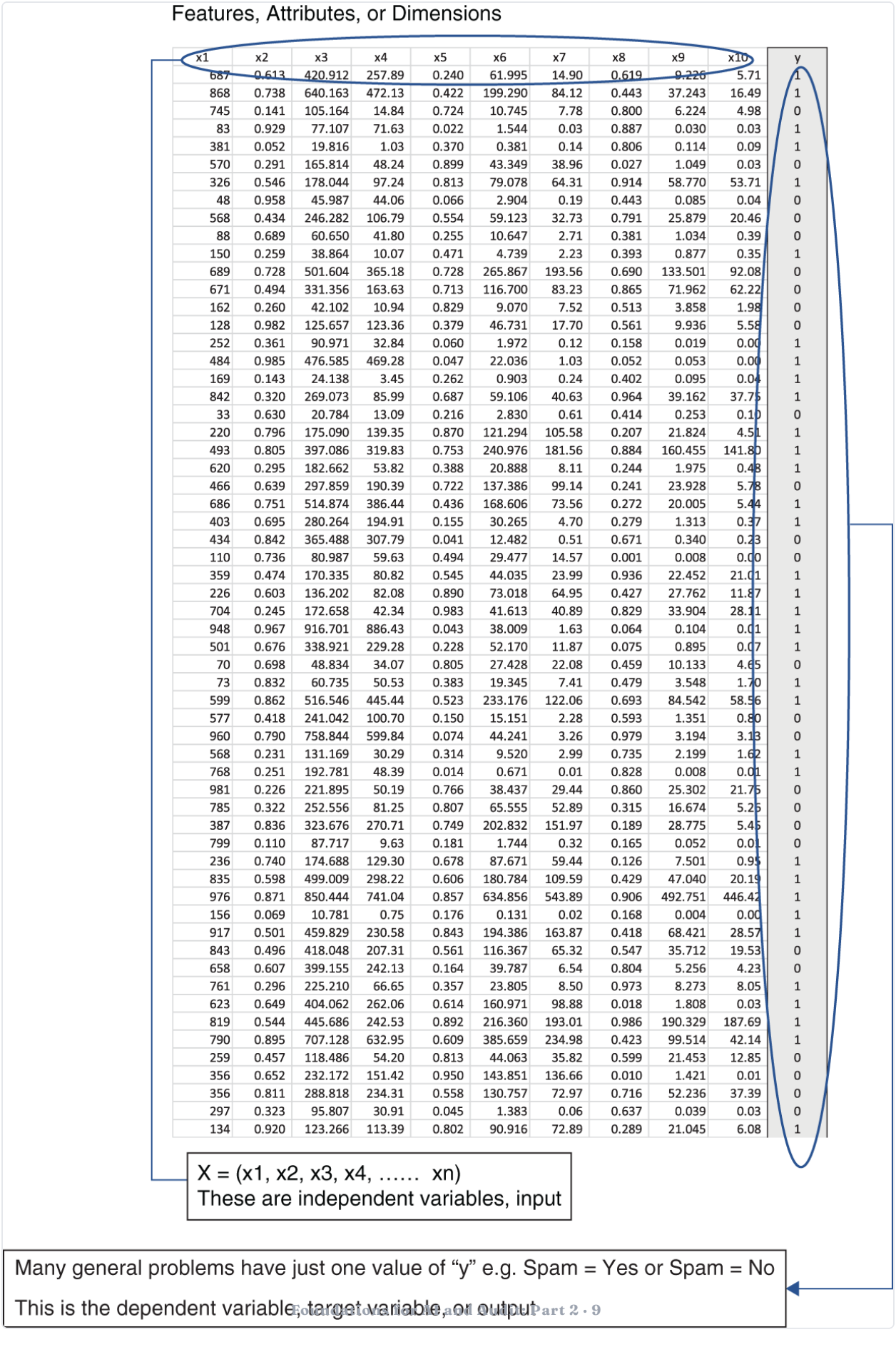
Here we run into a conceptual problem. The concept of pattern configuration as an assembly of properties and their values appears to be recursive and circular when we argue that properties themselves are pattern configurations of other properties, which are pattern configurations of other properties, and so on. It is as if nothing meaningful exists in the world except patterns, and perhaps that is why the human mind assigns meaning to things via pattern configuration. We can live with this recursiveness and circularity by consoling ourselves that it appears to be nature's strategy of achieving complexity from simplicity.

WHAT IS MACHINE LEARNING?

Based upon the above discussion, we discovered the following interesting concepts (see Figure 4.1):

There is something we are trying to predict. In the above example, it was rain. We can give it a name. Let us call it the output variable (also known as the dependent variable, target variable, or simply y).

FIGURE 4.1 DATA, FEATURES, AND TARGET



x1	x2	x3	x4	x5	x6	x7	x8	x9	x10	y
687	0.613	420.912	257.89	0.240	61.995	14.90	0.619	9.226	5.71	1
868	0.738	640.163	472.13	0.422	199.290	84.12	0.443	37.243	16.49	1
745	0.141	105.164	14.84	0.724	10.745	7.78	0.800	6.224	4.98	0
83	0.929	77.107	71.63	0.022	1.544	0.03	0.887	0.030	0.03	1
381	0.052	19.816	1.03	0.370	0.381	0.14	0.806	0.114	0.09	1
570	0.291	165.814	48.24	0.899	43.349	38.96	0.027	1.049	0.03	0
326	0.546	178.044	97.24	0.813	79.078	64.31	0.914	58.770	53.71	1
48	0.958	45.987	44.06	0.066	2.904	0.19	0.443	0.085	0.04	0
568	0.434	246.282	106.79	0.554	59.123	32.73	0.791	25.879	20.46	0
88	0.689	60.650	41.80	0.255	10.647	2.71	0.381	1.034	0.39	0
150	0.259	38.864	10.07	0.471	4.739	2.23	0.393	0.877	0.35	1
689	0.728	501.604	365.18	0.728	265.867	193.56	0.690	133.501	92.08	0
671	0.494	331.356	163.63	0.713	116.700	83.23	0.865	71.962	62.22	0
162	0.260	42.102	10.94	0.829	9.070	7.52	0.513	3.858	1.98	0
128	0.982	125.657	123.36	0.379	46.731	17.70	0.561	9.936	5.58	0
252	0.361	90.971	32.84	0.060	1.972	0.12	0.158	0.019	0.00	1
484	0.985	476.585	469.28	0.047	22.036	1.03	0.052	0.053	0.00	1
169	0.143	24.138	3.45	0.262	0.903	0.24	0.402	0.095	0.04	1
842	0.320	269.073	85.99	0.687	59.106	40.63	0.964	39.162	37.75	1
33	0.630	20.784	13.09	0.216	2.830	0.61	0.414	0.253	0.10	0
220	0.796	175.090	139.35	0.870	121.294	105.58	0.207	21.824	4.51	1
493	0.805	397.086	319.83	0.753	240.976	181.56	0.884	160.455	141.80	1
620	0.295	182.662	53.82	0.388	20.888	8.11	0.244	1.975	0.48	1
466	0.639	297.859	190.39	0.722	137.386	99.14	0.241	23.928	5.78	0
686	0.751	514.874	386.44	0.436	168.606	73.56	0.272	20.005	5.44	1
403	0.695	280.264	194.91	0.155	30.265	4.70	0.279	1.313	0.37	1
434	0.842	365.488	307.79	0.041	12.482	0.51	0.671	0.340	0.23	0
110	0.736	80.987	59.63	0.494	29.477	14.57	0.001	0.008	0.00	0
359	0.474	170.335	80.82	0.545	44.035	23.99	0.936	22.452	21.01	1
226	0.603	136.202	82.08	0.890	73.018	64.95	0.427	27.762	11.87	1
704	0.245	172.658	42.34	0.983	41.613	40.89	0.829	33.904	28.11	1
948	0.967	916.701	886.43	0.043	38.009	1.63	0.064	0.104	0.01	1
501	0.676	338.921	229.28	0.228	52.170	11.87	0.075	0.895	0.07	1
70	0.698	48.834	34.07	0.805	27.428	22.08	0.459	10.133	4.65	0
73	0.832	60.735	50.53	0.383	19.345	7.41	0.479	3.548	1.70	1
599	0.862	516.546	445.44	0.523	233.176	122.06	0.693	84.542	58.56	1
577	0.418	241.042	100.70	0.150	15.151	2.28	0.593	1.351	0.80	0
960	0.790	758.844	599.84	0.074	44.241	3.26	0.979	3.194	3.13	0
568	0.231	131.169	30.29	0.314	9.520	2.99	0.735	2.199	1.62	1
768	0.251	192.781	48.39	0.014	0.671	0.01	0.828	0.008	0.01	1
981	0.226	221.895	50.19	0.766	38.437	29.44	0.860	25.302	21.75	0
785	0.322	252.556	81.25	0.807	65.555	52.89	0.315	16.674	5.25	0
387	0.836	323.676	270.71	0.749	202.832	151.97	0.189	28.775	5.45	0
799	0.110	87.717	9.63	0.181	1.744	0.32	0.165	0.052	0.01	0
236	0.740	174.688	129.30	0.678	87.671	59.44	0.126	7.501	0.95	1
835	0.598	499.009	298.22	0.606	180.784	109.59	0.429	47.040	20.19	1
976	0.871	850.444	741.04	0.857	634.856	543.89	0.906	492.751	446.42	1
156	0.069	10.781	0.75	0.176	0.131	0.02	0.168	0.004	0.00	1
917	0.501	459.829	230.58	0.843	194.386	163.87	0.418	68.421	28.57	1
843	0.496	418.048	207.31	0.561	116.367	65.32	0.547	35.712	19.53	0
658	0.607	399.155	242.13	0.164	39.787	6.54	0.804	5.256	4.23	0
761	0.296	225.210	66.65	0.357	23.805	8.50	0.973	8.273	8.05	1
623	0.649	404.062	262.06	0.614	160.971	98.88	0.018	1.808	0.03	1
819	0.544	445.686	242.53	0.892	216.360	193.01	0.986	190.329	187.69	1
790	0.895	707.128	632.95	0.609	385.659	234.98	0.423	99.514	42.14	1
259	0.457	118.486	54.20	0.813	44.063	35.82	0.599	21.453	12.85	0
356	0.652	232.172	151.42	0.950	143.851	136.66	0.010	1.421	0.01	0
356	0.811	288.818	234.31	0.558	130.757	72.97	0.716	52.236	37.39	0
297	0.323	95.807	30.91	0.045	1.383	0.06	0.637	0.039	0.03	0
134	0.920	123.266	113.39	0.802	90.916	72.89	0.289	21.045	6.08	1

We understood that there are properties or associations of rain that help us determine what is rain or help us predict if it will rain or not. For example, properties that might inform us whether it is rain or not could be asking questions like: Is there water pouring down? Is it water? Is it coming from the clouds? etc. To predict if it will rain or not, we will use properties such as clouds, cloud type, moisture, or wind. Let us call these properties or attributes features. Features give us information about the target variable and are considered as the input variables or independent variables.

Each of the above features contains values. For example, temperature may contain a range of values, cloud type may be represented on a categorial scale (e.g., numbers 1 to 10, each representing a cloud type), and so on. This is obviously the **data**. We can think of it as the **training data**. Thus, features have data. Conceptualize a table with data in it such that each column represents each feature.

Imagine each row with values of features. Let us call that our **feature vector**.

Lastly, the most important thing is the relationship between features (the properties or attributes) among themselves and with the target variable. This relationship is what forms the patterns we are interested in. We can express this relationship as a mathematical function. Let us call this a function we are interested in finding. For example, it may look like:

$$\text{Will it Rain (Y, N)} = w_0 + w_1 * \text{Variable 1} + w_2 * \text{Variable 2} + w_3 * \text{Variable 3} + \ldots$$

Or written differently:

$$f(x) \text{ or } y = w_0 + w_1x_1 + w_2x_2 + w_3x_3 + \ldots ..$$

Here “w” is the weights assigned to each variable. You can think of weights as importance assigners – variables with more importance in predicting the output get a higher weight. This means that if we are predicting whether it will rain or not, the variable (e.g., moisture) that has the highest predictive information will have a higher weight. Once we find the weights that can represent our data, we will have the representative function.

In general, machine learning is about finding that function – that is, the function that links the features (input or independent variables) to the output variables.