Motivation for learning statistics: An example from fishery and aquaculture science

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Abstract

Teaching statistics to generalist students oriented toward a profession, rather than academic merits, may be challenging. As statistics courses also tend to have a low student appeal, tailoring a course toward this type of audience is demanding. Framed within the theory of statistical thinking and literacy, this article shows how an investigative process, using domain data and real-life examples, may facilitate meaningful learning and motivate students. Describing and reflecting upon the methods used, both in teaching and assessment, the article contributes to the practice of teaching statistics.

KEYWORDS: domain data, generalist students, investigative process, statistical literacy and thinking, teaching statistics

1. INTRODUCTION

I was hired as an Associate Professor in August 2018, and the first challenge that was thrown at me was to design and teach an introductory statistics course for bachelor students in the Fisheries and Aquaculture Science (FAS) program. FAS is an integrated and interdisciplinary program in which students are taught several topics related to fisheries and aquaculture. In this program, statistics is a requirement in the first year of study and serves as a basis for subsequent courses, such as economics and biology.

Due to the success of the fisheries and aquaculture industries, FAS students are in demand, and many students are employed in the industry after finishing their FAS bachelor's degree. A general characteristic of FAS students is their “vocational motive” [65], meaning that students focus on a career and the profession, rather than academic merits.

A challenge in any course is to tailor the course toward the target audience. Because of the interdisciplinarity of the program, FAS students are generalists rather than specialists. Also, the student group has a heterogeneous background. Some students come from the fisheries or aquaculture industries, while others come directly from high school—vocational or academic. Hence, some students have fresh knowledge of quantitative methods, whereas others are a bit rustier, but have a good understanding of the domain.

Other challenges are students' “statistics anxiety” [42] and the general low appeal of statistics [18], affecting students' motivations for learning statistics. To gauge their motivation, every year I ask students how many are taking the course because statistics are interesting and fun. Usually, no or very few hands are shown. Then I ask, how many are taking the course because they must. All hands are shown. As motivation affects student performance and educational efficiency [11], it is essential to design a course that cultivates meaningful learning [8] and thereby motivation for learning.

The question thus becomes, what is meaningful learning for these students? How can I design and teach a course that motivates students who are not—at least not initially—inclined toward learning statistics? In particular, how may the use of domain data and real-life examples provide meaningful learning and motivate students? This article will describe some of the methods used. I will reflect upon what has worked (or not), and thereby contribute with experience and practical examples of how others may approach teaching quantitative methods. The article is organized as follows: section two gives an overview of the course, and section three offers the theoretical lenses used in the article. Section four describes the method used to understand and improve the students learning, while section five describes some of the chosen approaches. This section also describes students' experiences through course evaluations. The article ends with some reflections on possible future directions of the course.

2. THE COURSE: STATISTICS AND METHOD FOR FISHERIES AND AQUACULTURE SCIENCE (FSK-1121)

The program FAS comprises a total of 180 credits divided into 6 semesters. The study program is defined as an interdisciplinary program, as it integrates different disciplines organized around a topic or theme [36,63]. The first year of FAS is an introductory year, in which students are familiarized with the philosophy of science, the domain (fisheries and aquaculture), chemistry, mathematics, biology, biochemistry and microbiology, economics, and statistics (Table 1). The subsequent semesters (3 to 6) are “single-subject” semesters of 30-ECTS. In the third semester, the course “Sustainable Fishery” (FSK-2020) is taught, which addresses sustainability issues in the management and utilization of wild marine resources. The course integrates different disciplines, including fisheries biology, fishing technology, resource economics, social sciences, and law [60]. Similarly, the fourth semester is “Sustainable Aquaculture” (FSK-2030), which gives an introduction to the farming of aquatic organisms from social science, economics, and ecology perspectives [61]. The fifth semester offers the course “Sustainable Seafood” (FSK-2040), which consists of seafood processing and sales, including economics, marketing, and trade [62]. The program has grown in popularity, and the size of the classes has increased from 35 in 2019 to over 50 in 2022.

TABLE 1 First year in the Fisheries and Aquaculture Science program.

Semester	10 ECTS	10 ECTS	10 ECTS	
1. Semester (fall)	FIL-0700 Examen Philosophicum	FSK-1100 Fisheries and aquaculture science	FSK-1101 Chemistry for fisheries and aquaculture science (5 ECTS)	FSK-1102 Mathematics and method for fisheries and aquaculture science (5 ECTS)
2. Semester (spring)	FSK-1120 Aquatic biology for fisheries and aquaculture science	FSK-1122 Biochemistry and microbiology for fisheries and aquaculture science	FSK-1121 Statistics and method for fisheries and aquaculture science (5 ECTS)	FSK-1123 Economics for fisheries and aquaculture science (5 ECTS)

The statistics course FSK-1121 introduces students to quantitative scientific methods and their use in fisheries and aquaculture. The focus is on basic statistical concepts and their use, including descriptive and simple inferential statistics. Topics include data collection, data analysis, and reporting. The course is relatively small (5 ECTS), and the norm for this size course is a minimum of 14 h of lecture/ seminar/labs during the semester (16 wk). The expected out-of-class workload is about 8 h per week [59]. Other related quantitative methods taught are “mathematics and methods” (FSK-1102), which introduces students to math relevant to biology and economics courses at bachelor level.

The objectives of the statistics course are 3-fold. First, there is the “instrumental” objective of learning the concepts, the process, and the craft of conducting statistical analysis. Second, the course is meant to contribute to students becoming critical consumers of statistics, which requires an understanding of the activities that produce them. Finally, in the long term, there is an ambition to give students the necessary skills and courage to choose a quantitative method in their subsequent work, for example, master theses.

The course is developed through a "recursive ongoing analysis" [45]. Recursivity is a non-linear process in which the design and procedure unfold as the study proceeds, or in this case, as the course develops. Thus, it is a path designed to "loop back and forth between data collection and analysis in a carefully constructed and documented manner" [22:2]. Despite the dynamic process, the method is systematic, logical, and cumulative. Hence, the development of the course is a recursive process between development, evaluation, and adaptation.

3. STATISTICAL THINKING AND LITERACY

As data are easily available and more easily produced or misrepresented than ever before, statistical literacy and thinking are of utter importance. With "fake news" and "alternative facts," understanding numbers, graphs, and tables has become crucial. Even those not formally trained in quantitative tools should be able to recognize poor-quality information and bad statistical analysis. Recognizing these situations can prevent bad statistics from influencing our opinion of the world [32].

The course is set within the general framework of statistical thinking and literacy. Despite several definitions, how to operationalize statistical literacy and thinking is not widely agreed upon [69]. A principle is not to teach statistics as "an unrelated collection of formulas and methods," but as "a problem-solving and decision-making process" [10:6]. This entails understanding the statistical process, including posing questions, collecting data, testing assumptions, analyzing data and finding patterns, interpreting, and making inferences [12,21,43,67,68], but also "developing understanding of the more relevant ideas of statistics and the interconnections among them" [40:325], such as variation and the role of chance.

Students should also be able "to understand and critically evaluate statistical results that permeate our daily life" [Wallman 1993:1 in 19:2–3]. Thus, even if students do not have their own research projects, they should be able to critically interpret results from studies and media reports [6,44].

Vermunt and Donche (2017) summarized the four patterns of student learning. Reproduction-directed learning, undirected learning, meaning-directed learning, and application-directed learning. In reproduction-directed learning, students memorize material to pass the test. It is a step-by-step procedure that does not offer a deeper understanding of the material. In an undirected-learning approach, students do not know how to approach the study at hand. This is particularly seen in the transition from, for example, secondary school to higher education; thus, these students rely heavily on guidance [65].

In a meaning-directed learning pattern, the students obtain a deeper understanding of the material and connect what they learn to a larger context. Students engage critically with the material, but more importantly, they have an internal motivation for learning. In application-directed learning, students link what they learn to the real world. In terms of FAS, students would apply what they learn in class to their work experience or what they have learned in other classes [65].

My objective is to move students from merely reproducing and remembering facts for passing tests to an approach in which students discover relationships between what they learn and the world outside. In this way, students construct their own knowledge by linking abstract statistical concepts to real-life problems within a familiar domain of interest. This then sparks an interest in and motivation to learn statistics. Moreover, using domain data also teaches students about the domain they are about to enter and adds value outside the scope of this course.

4. METHODS USED TO UNDERSTAND AND IMPROVE THE STUDENT EXPERIENCE

This article uses the course FSK-1121 as a case and is based on two sources of data: participatory observations and course evaluations. Participatory observations took place in class, as I am both the designer and the instructor of the course. This method offers a rich description of human behavior and experiences about a phenomenon [45] and therefore gives me a unique insight into the FAS program and, in particular, the statistics course. During and immediately after class sessions, notes were taken on what approaches did or did not work, questions asked, and issues raised. Notes directly linked to course content were recorded in the class PowerPoints to be readily available for revision, whereas more pedagogical issues were recorded in a separate document. These notes were further expanded upon in the end-of-the-year teacher evaluation of the course, in which the instructor reflects on teaching methods and possible improvements.

The other source of data for this article was the oral and/or written course evaluations. In the first year, in 2019, the course did not have a final written course evaluation. Rather, I talked and discussed with students about course design, teaching activities, and what they struggled with. The class ombudsperson was a particularly important source of information and a sounding board. In 2020 and 2021, the course evaluations were both oral, in the form of continuous dialogue, and written end-of-the-year course evaluations.

Written course evaluations are a part of the systematic evaluations carried out annually, using an online survey tool (www.nettskjema.no). In 2020, the response rate of the student survey was 40% (18/47 students), while in 2021 it was 60% (28/47 students). In 2020, as I wanted to see how well the exam was aligned with the teaching, the evaluation was sent to the students after the final exam. One reminder was sent. However, the choice of timing of the evaluation could have affected the results, as early responders tend to evaluate more positively, than late responders. This suggests the possible presence of nonresponse bias [16].

In 2021, the evaluation was carried out in the last lecture, before the final exam. The response rate increased. Still, the nonresponse rate was 40%, which reflects the no-shows in class. No reminders were sent. As attendance is not obligatory, the response rate could have been improved if the survey had been sent to the absentees. However, as the survey is anonymous, the no responders were not known.

The written student evaluations consisted of two parts: (1) structured questions about course content and work forms, student participation and effort, as well as general satisfaction with the course, and (2) open-ended questions in which the students could elaborate more on their answers and provide suggestions for improvements. The student evaluation took about 10 min.

5. TEACHING APPROACH: PROCESS-AND DOMAIN-ORIENTED

So, how can I provide meaningful learning and motivate students for learning statistical thinking and literacy? In the following, I will describe how I approached this in practice, some of the challenges I encountered, how I opted to solve them, and how this was experienced by the students.

5.1. Teaching statistics as an investigative process using domain data

Wanting to teach students lifelong, useful, applicable, and transferable skills [15], I focused on the following question: what skills do the students need in their professional life, further studies, and life in general? And how to teach these skills? A novice statistics teacher needs crutches. In my search for some practical guiding principles for teaching statistics, I found the Guidelines for Assessment and Instruction in Statistics Education (GAISE) useful [10,68], in particular, the following principles:

1. Teach statistics as an investigative process of problem-solving and decision-making.

2. Introduce students to a domain using real data and with a purpose.

(Other principles were also adopted, for example, the use of software to explore concepts, but in this article, the focus is on the investigative process and use of real, domain data). These principles would teach students the value of statistics as an investigative process of problem-solving and decision-making [10,20,58]. Using real data would give students experience with real-life numbers and domain knowledge [1,13,24,41], but could also lower students' statistical anxiety [33]. Moreover, the chosen tasks had to be meaningful to my students—trivial tasks do not motivate learning [35,66]. An advantage of the FAS program is its clear industry focus, which delimits and focuses on the context and the data to be used.

The course covers the following themes:

1. Problem to be solved: how to pose statistical questions and research questions.

2. Study design: how to design an experiment or survey, including questionnaires.

3. Tools: what statistical tools will help us answer our questions (incl. software).

4. Data collection: including selectivity, representativity, informed consent, and ethical issues.

5. Statistical analysis: including basic hypothesis testing, variance, and correlation analysis, simple regression analysis, and most common non-parametric tests.

6. Presentation, interpretation, and reporting of statistical analysis and results.

Initially, I wanted the students to collect their own survey data. This would require students to (1) design research-and survey questions, (2) collect data, and (3) clean, format, quality check, and securely store data. Although these are important skills, it was found to be too time-consuming, and time is unfortunately a major constraint in this course [27,39].

Rather than collecting our own data, we had to rely upon secondary and pre-cleaned data. Luckily, the Norwegian context supplies many data sources for fisheries and aquaculture statistics [see e.g, 5,17,46], which offer “data about which at least some answers have already been given so that instead of being forced to fish for interesting phenomena in an empty ocean, students can follow a trajectory from exploration to valid argument” [23:9]. A drawback of not collecting our own data, however, was that the discussion around data collection and ethical issues became somewhat theoretical.

Still, keeping an eye on the statistical process, lectures were designed to show students how statistics could be used to explore phenomena. The following is an example used in class. The example does not cover all the steps above and does not necessarily follow the same order (some steps are not mutually exclusive) but focuses on the investigative process and the power of storytelling as a pedagogical tool. This example also makes use only of descriptive statistics. The point of departure for the class session was a newspaper article stating that the number of fishers was declining (Figure 1). An important point in the article was "the greying of the fleet." That the average age of fishers had increased, as recruitment of young fishers had failed. Subsequently, some fleet segments had, for periods, relied upon foreign employment [7,56].

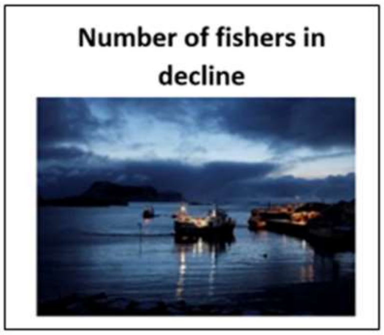

FIGURE 1 Number of fishers in decline [modified from 4,34].

The students were then presented with a good news story from the Ministry of Fisheries in 2018, which stated that the number of fishers had increased, and a graph showing the increase from 2015 to 2017 (Figure 2). According to the Minister, both the number of fishers and fishing boats in Norway were increasing. It was "very good news, that again this year there are more people who want to become fishers" [37]. This was indeed good news in an industry that was struggling with poor recruitment [53].

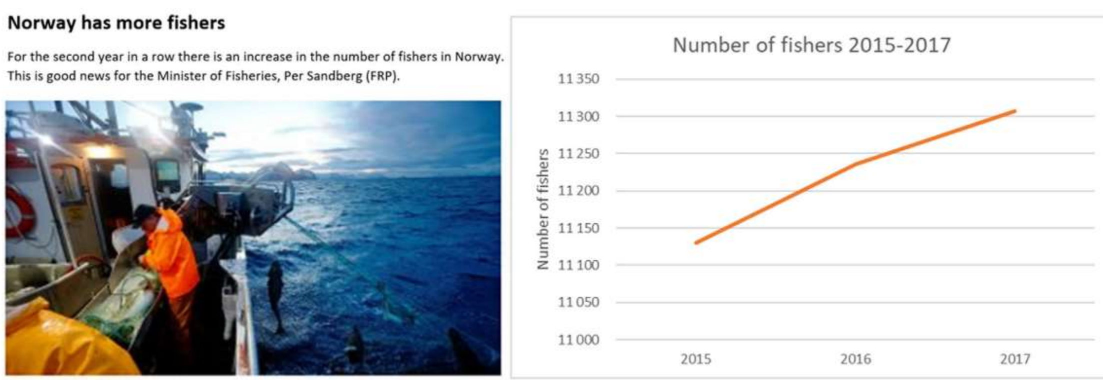

FIGURE 2 Increase in the number of Norwegian fishers [modified from 17,37].

After being presented with "the recruitment problem" and the "good news," the students were introduced to existing theories, hypotheses, and empirical data related to this phenomenon. A short presentation was given about fisheries recruitment and employment theories and the development of these since the 1970s [29,30,56].

The first question the class was asked to reflect upon was, "in terms of recruitment to the fishing fleet, what could be a statistical question, and potentially a research question? And why?" After discussing in pairs, a typical answer would be, "What has been the trend in the number of fishers?" or "What has been the development of the number of fishers under the age of 30?" Although not entirely wrong, it is the variation in the dataset that is of interest and offers interesting statistical inquiry [31]; which was what I was nudging the students toward. Thus, to lead the students, I asked: "given the Minister of Fisheries' claim of an increased number of fishers, and given the increased average age of fishers, how would you explore the ministers' claim?” Again, after discussing in pairs, some students argued that they would compare the number of fishers in different age groups over years. Collectively we then developed the following, and more interesting, statistical question: “How has the number of fishers in different age groups changed between 2013 and 2017?” and “What implications does our finding have in terms of recruitment policies in the Norwegian fishing fleet?”

Second, the students were presented with the actual numbers of fishers from the official fisheries registry data, available from the Directorate of Fisheries (DoF). The official fisher registry registers Norwegian citizens who work as fishers [25] and contains personal data such as name, birth year, type of fisher (full-or part-time), county, municipality, and when they were entered or deleted from the registry [17]. The data were presented in an Excel file to the students and used for the in-class analysis. We started by discussing the representativity of the data. For instance, given that the registry is only for Norwegian citizens or people with landed immigrant status, and given that recruitment problems lead to increased reliance upon foreign labor, are there parts of the fishing fleet that the data in the registry would not represent? This required me to define what representativity meant but also to convey an understanding of the characteristics of the various fishing fleet segments—taught in other courses.

Third, we turned to the analysis of the question, “How has the number of fishers in different age groups changed between 2013 and 2017?”, using the data from the DoF. Through simple descriptive statistics and graphical displays, we collectively produced tables and figures in Excel to examine and nuance the Minister's claim. Figure 3 shows the table and figure produced and illustrates how the share of fishers in different age groups changed between 2013 and 2017. The picture shows that the increase in the total number of fishers is not evenly distributed across all age groups. Based on this figure, the students were asked in pairs to interpret the meaning and the implications of the figure in relation to our research question. Most students recognized that the increase in the number of fishers under the age of 30 was less than the increase in the number of fishers aged 70 y and over. However, they struggled to make the inference that the total number of fishers was increasing, not because many young people were entering the fisheries, but because old fishers were not retiring (the normal retirement age in Norway is 68 y).

Age group	Number of fishers 2013	Number of fishers 2017	Change 2013-2017
<20	200	193	-4 %
20 - 29	1491	1674	12 %
30 - 39	1604	1633	2 %
40 - 49	2196	1903	-13 %
50 - 59	2077	2079	0 %
60 - 66	1272	1099	-14 %
67 - 69	422	407	-4 %
>=70	297	485	63 %

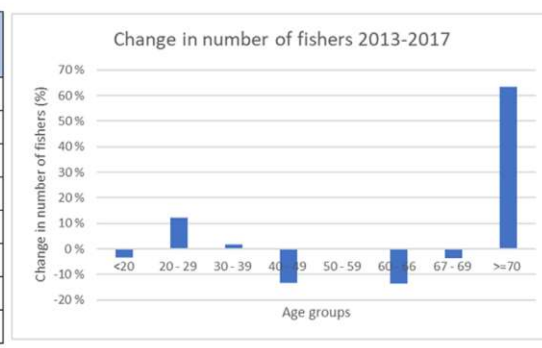

FIGURE 3 Developments in different age groups in the fishing fleet 2013–2017 [17].

Finally, to round off, we discussed the implications of our findings in terms of recruitment policies. First, the students were presented with the long-term trends in the number of fishers (Figure 4). Then we discussed how Figure 2 misrepresented the general downward trend by showing only two years and the over-extension of the y axis. Finally, Figure 4 combined with Figure 3 led to a plenary discussion about the greying of the fleet and its policy implications in the long term.

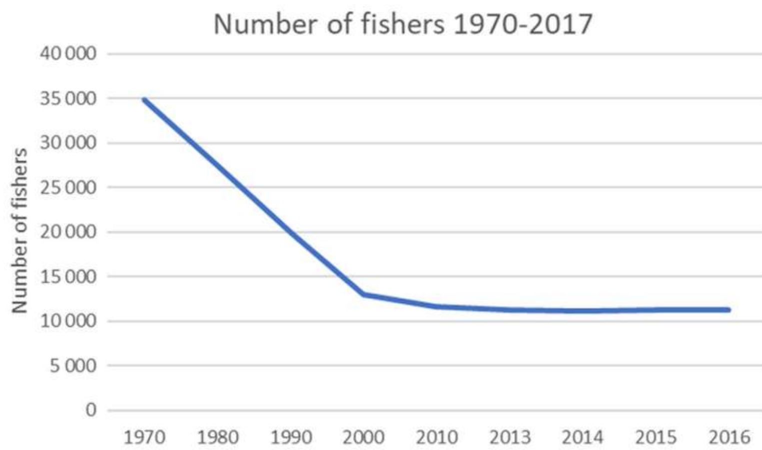

FIGURE 4 Development of the number of fishers between 1970 and 2017 [17].

To summarize, the example shows the use of an investigative process approach in a class session. It shows how to develop statistical questions and how to relate these to existing theories and empirical data within the field. It also shows how data were obtained and analyzed using simple descriptive statistics and visual graphics. Finally, the results were interpreted in terms of context and policy implications.

5.2. Use of domain data in assessment

The example in the previous section showed domain data used in an investigative process in an in-class session. The following examples will illustrate how domain data and real-life problem-solving are applied throughout the course by inclusion in work requirements and examinations.

The first example (Work requirement 2, Exercise 3) was inspired by the work of the World Fish Centre in Asia [3]. To make the example less obvious, the place name was changed. The objective of this example was 2-fold. First, the students had to show that they had mastered basic statistical tools, such as correlation and simple regression. Second, they had to show that they could make a simple interpretation of the results, based on knowledge gained in other courses. For simplicity, the time series nature of the data was ignored but was discussed in class.

5.2.1. Work requirement 2, Exercise 3

Lake Sadim is an important source of protein for the people living around it. In recent years, there has been a ten dency for increased effort (measured in the total number of gillnets) and a decline in catch per unit effort (CPUE = catch [kg]/gillnets [number of]). If this trend continues, this could be detrimental to the resources in the lake but also to the livelihoods of the people around it. To control effort and the resource situation, you want to study the CPUE in the lake for the last 21 years. Based on the dataset below, perform the analyses (see Table 2).

TABLE 2 Dataset Lake Sadim.

Year	No. of fishers	No. of gillnets	CPUE	Year	No. of fishers	No. of gillnets	CPUE
1	12	90	1400	12	44	100	1000
2	33	260	900	13	52	260	1050
3	140	1800	250	14	56	420	980
4	160	1600	110	15	32	210	1150
5	45	230	1400	16	12	75	1390
6	111	700	520	17	45	286	1100
7	87	600	800	18	78	500	700
8	75	700	900	19	90	585	680
9	66	600	960	20	23	140	1200
10	122	700	250	21	13	82	1400
11	11	120	1320				

a. Using a graphical illustration, what would you say about the relation between the number of fishers and the CPUE in the lake? **Answer:** From the figure below, there seems to be a strong, negative relationship between the number of fishers and CPUE in the lake. That is, as the number of fishers increases, CPUE decreases, or the catch per gillnet decreases (see Figure).

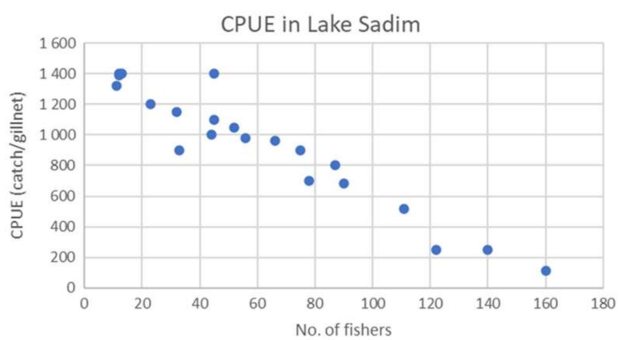

FIGURE 5 CPUE in Lake Sadim.

b. What is the correlation between the number of fishers and CPUE, and how will you interpret your results? **Answer:** From the table below, we observe a strong, negative correlation between the number of fishers and CPUE with R = -0.9573. That is, as the number of fishers increases, the CPUE decreases, or the catch per gillnet decreases (see Table 3)

TABLE 3 Correlation analysis output.

	No. of fishers	*No. of gillnets*	*CPUE*
No. of fishers	1		
No. of gillnets	0.911710324	1	
CPUE	−0.957309198	−0.861954245	1

c. Find the straight line that best fits the data ($y = \alpha + \beta x$) by using a simple regression analysis of the number of fishers and CPUE. Interpret your regression line. **Answer:** The regression line y = 1465.81–8.66x tells us that when the number of fishers (x) increased by one, the CPUE (y) decreased by 8.66 kg/gillnet (see Table 4).

TABLE 4 Regression output.

Summary output								
Regression statistics								
Multiple R	0.957309198							
R^2	0.9164409							
Adjusted R^2	0.912043053							
SE	116.7329578							
Observations	21							
ANOVA								
	df	*SS*	*MS*	*F*	*Significance F*			
Regression	1	2 839 561.582	2 839 562	208.384	1.07863E-11			
Residual	19	258 905.0851	13 626.58					
Total	20	3 098 466.667						
	Coefficients	*SE*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95,0%*	*Upper 95,0%*
Intercept	1465.814008	45.20850775	32.42341	4.25E−18	1371.191514	1560.436502	1371.192	1560.437
No. of fishers	−8.662658123	0.600093633	−14.4355	1.08E−11	−9.918668531	−7.406647714	−9.91867	−7.40665

d. Given theories about open access resources, what do your findings say about the potential future resource situation in the lake, and what could be done about it? **Answer:** The development in the lake is worrying, as CPUE (catch [kg]/gillnet) is in decline. Thus, to maintain the level of catches at the individual level, the individual fisher needs to increase effort (e.g, the number of gillnets). Over time, this situation may result in overexploitation and the Tragedy of the Commons. To avoid over-exploitation, the total fishing effort must be controlled by controlling the number of fishers and/or controlling the number of gillnets allowed per fisher. Depending upon the management system in the lake, this may or may not be possible.

The examples below show how I used domain knowledge and data from aquaculture in the exam. As time was limited (four hours), the dataset was organized and cleaned. The exam question was based on a real-life case of a company, WildernessFish Ltd., which went bankrupt because they did not control their biomass. They sold more fish than they produced. A challenge was that we did not have raw data for the case; however, a colleague had been involved in WildernessFish and had the necessary biological parameters from which we simulated a close-to-real-life dataset. As with the example above, the objective of the exercise was for the student to show that they had mastered basic statistical tools, such as hypothesis testing and ANOVA, but also to reason based on the results.

5.2.2. Question 5-final exam

You are the general manager at WildernessFish Ltd., which produces and sells wild-caught char from a lake nearby. Wild fish are caught in pots when they are approx. 50 g and farmed in tanks until a weight of between 300 to 1000 g is achieved. You have eight tanks for growing the fish to marketable size. Each tank contains about 2000 fish. The market usually demands the following size categories: 300–400 g, 400–600 g, and over 600 g. It takes approx. 8 months to produce a fish of 500 g. WildernessFish Ltd. receives about NOK 74/kg, which is resold in shops as a delicacy for NOK 250/kg (see Figure 6).

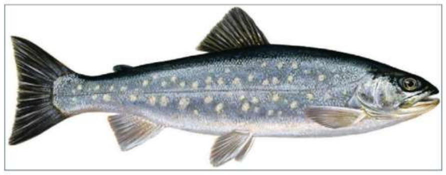

FIGURE 6 Arctic char [38].

WildernessFish Ltd. has received an order from a wholesaler for 500 kg char to be delivered in 14 days. The customer wants fish that are, on average, over 400 g. You think that tank 2 may contain fish of this size. To find out if you should start slaughtering from tank 2, you take a random sample of 20 fish from the tank and run a hypothesis test. Use the dataset below to conduct the analysis (see Table 5).

TABLE 5 Dataset WildernessFish Ltd.

Obs.	Tank 1	Tank 2	Tank 3	Tank 4
1	387.14	337.01	892.56	608.77
2	467.33	535.58	691.85	440.81
3	331.13	632.81	957.73	561.25
4	353.86	628.75	947.99	360.93
5	138.13	726.83	948.36	377.39
6	380.55	442.86	529.76	542.41
7	337.10	405.29	571.60	427.50
8	359.02	208.95	1088.40	514.91
9	392.19	512.58	502.68	474.56
10	402.85	930.49	496.01	563.59
11	505.35	364.31	843.72	543.45
12	342.81	246.48	500.34	355.58
13	246.42	175.09	376.05	462.17
14	470.65	830.85	429.24	526.87
15	312.35	433.85	664.84	384.65
16	378.90	251.88	669.42	421.00
17	108.58	529.60	1309.63	483.58
18	239.05	493.40	759.50	387.58
19	278.11	703.76	81.81	558.53
20	310.46	457.31	495.36	493.26

1. Formulate the null and alternative hypotheses **Answer:** H0: $\mu \leq 400$ g and Ha: $\mu > 400$ g.

2. Which test do you want to use, and why, to test the hypothesis? **Answer:** A t-test because the population SD (σ) is unknown, but also because $n < 30$.

3. Does your data satisfy the assumption of normal distribution, and can you apply parametric statistics to your data? **Answer:** The Boxplot below shows that the data are relatively normally distributed (median and mean are close to each other), and there are no outliers. Thus, we can use parametric statistics (see Figure 7).

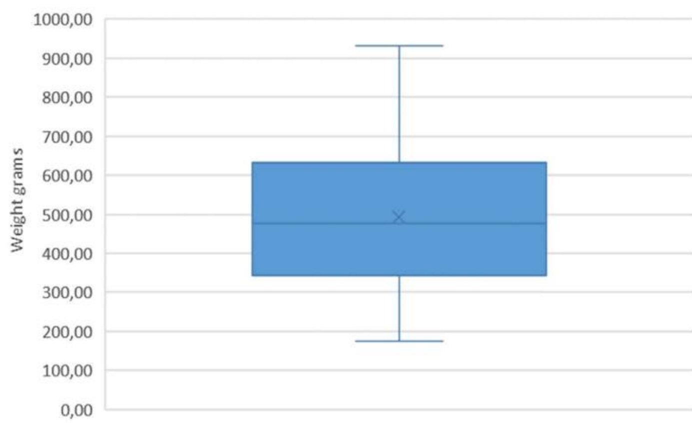

FIGURE 7 Boxplot for testing normality.

5.2.3. Question 6-final exam

You released small, wild-caught fish in tanks 1, 2, and 3 at the same time when the fish were approximately 50 g. However, because of problems with cannibalism, there may be uneven growth in the three tanks. You need to test whether the mean size of the fish varies in the three tanks. Given the dataset above, complete the following exercises below.

1. What type of analysis would you run and why? **Answer:** ANOVA to test whether the three groups have the same mean.

2. Formulate the hypotheses. **Answer:** H0: $\mu 1 = \mu 2 = \mu 3 = ... = \mu k$ and Ha: at least one of the population means (μ) is different (it is unknown which one).

3. Run an analysis (confidence level 95%) to see whether the size varies in the three tanks and interpret your results. **Answer:** From the output demonstrated below, we see that $F = 13.889 > Fc = 3.158$; we reject the null hypothesis that the mean size in the three tanks is the same. We obtain support for our alternative hypothesis that the average size is different in at least one tank. Thus, there seems to have been uneven growth in the three tanks, which could be due to cannibalism (but there could also be other factors) (see Table 6).

TABLE 6 Output ANOVA.

ANOVA: Single factor						
Summary						
Groups	***Count***	***Sum***	***Average***	***Variance***		
Tank 1	20	6741.974	337.0987	10 099.01		
Tank 2	20	9847.683	492.3842	42 245.85		
Tank 3	20	13 756.85	687.8427	81 097.19		
ANOVA						
Source of variation	***SS***	***df***	***MS***	***F***	***P-value***	***F crit***
Between groups	1 235 593	2	617 796.5	13.8891	1.22E-05	3.158843
Within groups	2 535 399	57	44 480.68			
Total	3 770 992	59				

These cases illustrate how real-life examples and data from the fisheries and aquaculture domain are used in the FSK-1121 course for assessment. The first case introduced the students to the domain of fisheries management in inland lakes, whereas the second introduced the students to a real business case. The connections to theories and concepts taught in other classes are also of importance, such as the Tragedy of the Commons [26] and fish biology.

5.3. Course evaluations and course adjustment

The course is continuously evaluated and adjusted. In the first year, in 2019, the course was evaluated through close and continuous dialogue with students and the class ombudsperson. In 2020 and 2021, the course was also subject to written end-of-term evaluations submitted by students. According to the students, they were satisfied with the course. In 2020, 100% of respondents were either satisfied or very satisfied, while in 2021 the number was 96.5%. Most of the students agreed that the course taught them analytical skills, statistical concepts (ideas), and methods, as well as practical skills (Table 7). In 2020, 94% agreed that the instruction had been engaging, whereas this number dropped to 71% in 2021. The evaluation in 2021 added a question on statistical understanding. Eighty-two percent of the student respondents agreed that the course had given them a better statistical understanding. [54,55].

The evaluations did not explicitly evaluate statistical thinking or literacy, but students liked that the class was not a "cookbook" in which the point was to memorize formulas and procedures. As one said,

> *I like that the focus is on understanding how to find and use things, and not on having to memorize all the formulas and methods. I have also liked the work requirements, they reflect what we have gone through and are a great way to test how you are doing [47].*

TABLE 7 Course evaluation 2020 and 2021 [54,55].

Do you disagree/agree with the following statements about the output of the course?	Disagree	Somewhat agree	Agree
Course evaluation 2020			
a. The course has taught me to analyze problems	6%	17%	78%
b. The course has taught me facts, concepts, and methods	0%	33%	67%
c. The course has taught me practical skills	6%	17%	78%
Course evaluation 2021			
a. The course has taught me how to analyse problems	7%	29%	64%
b. The course has taught facts, ideas, and methods	4%	32%	64%
c. The course has taught me practical skills	7%	21%	71%
d. The course has given a better statistical understanding	4%	14%	82%

The use of real domain data was well received by the students, as one student said: "for many, this is the first time they get examples from the fisheries and aquaculture industry" [49]. Students also found that "Work requirements that can be related to working life made the subject more exciting" [48]. Others pointed to the motivational aspect of using domain data, as "relevant and good examples and cases along the way make it extra motivating" [50]. Still, more domain-relevant datasets and exercises were called for [51,52].

Motivation is difficult to measure [28], but effort or hours spent working on the subject could be used as a proxy for motivation. In 2020, about 50% of the students worked between zero and five hours per week on the course. The remainder spent 5 h or more. In 2021, 89% spent between zero and five hours, and 11% more than five hours. For a four-month course, this would amount to a maximum of about 80 h (including class sessions) for the majority. The norm for a 5-ECTS course is between 125 and 150 h [57]. Hence, most students spent less time working on this subject than what is expected (see Table 8).

The low effort in the class is also evident in the student self-evaluation of their own efforts. In 2020, 89% agreed or somewhat agreed that they could have worked more on the course. This number was 100% in 2021 (Table 9).

TABLE 8 Effort, hours spent, on the course in 2020 and 2021 [54,55].

Approximately how many hours a week on average did you spend working on this course, including lecture/seminar attendance?	2020	2021
0–5 h	50%	89%
5–10 h	44%	11%
10+ h	6%	0%
	100%	100%

TABLE 9 Self-evaluated effort in FSK-1121 in 2020 and 2021 [54,55].

I could have spent more time working on this course	2020	2021
Disagree	11%	0%
Somewhat disagree	0%	0%
Somewhat agree	39%	54%
Agree	50%	46%
	100%	100%

Although self-evaluation of effort and hours spent on the course may indicate work effort, as it does not take into account varying efficiency of study and subjectivity in self-reporting, these measures are not precise measures for motivation [11]. Students' effort in one course is related to their total workload. Thus, reported lower effort in this course may also be an indication that other courses are too demanding.

6. THE WAY FORWARD

Given the experiences so far, have I offered meaningful learning to the students, and have I been able to motivate these students toward learning statistics? Moreover, have I contributed to their statistical literacy and thinking by teaching statistics as an investigative process using real domain data?

So far, students seem satisfied with the course, and the course seems to have given the students the basic craftmanship of statistics, which is also supported by students passing work requirements and a few students failing the final exam. In 2019, no students failed, the average grade was a C, but almost 44% received an A or a B. As the first year of running the course, this was a year of calibration for both instructors and examiners, which explains the high grades. By 2021, 9% of students failed, the average grade was a C, and the share of As and Bs had dropped to 37%, which is more in line with the expected distribution of grades [14,64].

A large number of hours of instruction should also be kept in mind. The norm for this size, of course, is about 14 h of instruction [59], whereas we offered 38 h of lectures and seminars over the course of four months (Feb-May). Although beneficial for the students, from an administrative point of view, this is not sustainable in the long run. We are therefore working toward a flipped classroom approach. Prior to in-class sessions, students will read the curriculum and watch short, theoretical videos that introduce them to the theme at hand. They will also be presented with a few relevant domain-specific statistical problems to ponder. The in-class session will first recap the theory and then solve and discuss these presented problems. Hopefully, this will be less demanding on resources, while maintaining the grade point average.

The methods of combining theory and practical examples using domain data have worked well and seem to be a motivational factor in the course. This approach will be further expanded and developed, as we are building a database with fisheries and aquaculture datasets for in-class problem-solving, work requirements, and exams. Having real-life examples available will also ease the work for new instructors while securing the industry relevance of the course.

To truly teach the course as an investigative process, it needs more development. Having limited knowledge about students conducting entire investigations [39], and the size limit of the course, the course design will require careful choreography between the various stages in the process. Hence, we are developing a portfolio assessment with individual, but connected work requirements that cover the entire process. As of now, themes are taught as rather separate pieces, which is exacerbated by the atomistic approach of most textbooks. Thus, we are also in the process of making a supplementary curriculum with a problem-based and process-and domain-oriented approach [2]. This curriculum will mirror the investigative process.

A portfolio approach will address some of the present shortcomings in reporting and communicating results. As most of the students end up in the industry, we will focus on scientific report writing. Each work requirement will be designed as a section in a report: the problem to be addressed and research question, study design, data collection (including selection and critical reflection around representativity and generalizability), analysis, as well as interpretations (discussion).

As noted in the results section, a drawback of not collecting our own data was that the discussion around data collection became rather theoretical. Although challenging and time-consuming, data collection must be included in an efficient and time-wise manner. One approach is to let students collect data from existing fisheries and aquaculture databases. This would entail both numerical and categorical data, which would require some degree of data cleaning and formatting. As downloading existing data does not teach sampling, we will have to go outside our investigative process to teach sampling techniques and the effects of these. Inspired by Gapminder, we will use a game-based learning platform to sample data in class. We will ask questions for which we have some statistics, such as "What share of all plastic waste in the world ends up in the oceans?", or "Globally, people eat an average of 6 kg of beef and veal a year. How much fish is consumed on average per person?" (www.gapminder.org). As our sample is small and not randomized, it is likely to depart from the results of Gapminder, which allows for discussion of the results and effects of sampling.

The length of the course is a real challenge. A too-condensed course may reduce the students' understanding of the subject matter [9]. Also, statistics tend to be "inserted into curricula as a single-semester course"; yet, as training in the analysis of aggregate data, this will "undoubtedly require more time" [23:2]. A solution could be to integrate statistics into other courses continuously, or at the very least, use data and concepts that students are, or will become, familiar with in other courses.

This article has described my approach to teaching statistics to generalist students using a process-and domain-oriented approach. It has described how the course has been developed and implemented, as well as future plans for the course. Through meaningful learning, I attempt to move the students from reproduction-directed or un-directed learning approaches to a meaning-or application-directed learning approach [65]. That is, from just memorizing methods and rules to discovering the relevance of what they learn in the course to real-life problems in the industry. The present approach seems to motivate students for learning statistics. However, in terms of statistical thinking and literacy, it is difficult to say whether I have succeeded. My long-term ambition is to give the students the skills and courage to choose quantitative methods in the future. Whether this will materialize, however, remains to be seen.

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