An Actionable Knowledge Representation for Popular Fundamental Investment Strategies: The CANSLIM Case

Full Paper

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Abstract

Individual investors consistently underperform relevant investment benchmarks. Consequently, a considerable body of literature of fundamental investment strategies targeted towards this audience emerged. Several online platforms provide operationalization of these strategies in the form of stock screeners. However, each platform must use its own interpretation of the strategy as no central knowledge repository exists. Arguing that ontologies standardize the concepts relevant to a domain and enable knowledge sharing among domain users, this paper seeks to explore that viability of an ontology as a knowledge representation method to represent fundamental investment strategies. Our efforts herein go beyond representing the concepts and inter-concept relationships that are descriptive of fundamental investment strategies, as we also demonstrate that ontologies using SWRL rules can deploy these strategies as stock pickers (also referred to as stock screening). We use the CANSLIM strategy as a case, modeling and executing it on simulated data using our ontology and Semantic Web Rule Language (SWRL).

Keywords (Required)

Ontologies, Fundamental Investment, Finance, SWRL, OWL, Context-Aware Systems

Introduction

Investors in the capital markets are classified as “individual investors” and “Institutional investors.” The former refers to investors who manage their own equity portfolios, and the latter refers to professionals who act as intermediaries to invest individuals’ savings (Brennan 1995, p. 831). Studies in finance and business journals concerning the notoriously poor performance of individual investors abound. Individual investors consistently underperform relevant benchmarks (Barber and Odean 2000; Bondt 1998) and constitute 37.3% of Equity holdings in the United States (Grainger Inc. 2016). While the various pathologies plaguing individual investors are beyond the scope of this paper, we do consider the fact that this notorious underperformance has motivated a considerable body of literature on fundamental investment strategies in the form of equity stock selection guidelines. For example, the popular online and social investment platform MeetInvest which provides a customized implementation of some 52 popular investment strategies within a powerful stock screening tool for individuals. A similar service, Uncle Stock, provides its own implementation of several fundamental investment strategies in the form a stock screening tool. Of course, many popular strategies are available across platforms such as Joseph Piotroski’s F-Score strategy. However, the implementation of each strategy varies on each platform as platform designers augment the original strategies with proprietary components. In short, the knowledge embedded in popular fundamental investment strategies does not reside in a standardized format. Another issue is that popular accounts of fundamental investment strategies abound in the form of books and tutorials. Several automated stock screening platforms incorporating many of these strategies exist. However, these services offer their own idiosyncratic interpretations of these strategies with no clearly defined representation format from which to draw.

Arguing that ontologies standardize the concepts relevant to a domain and enable knowledge sharing among domain users, this paper seeks to explore that viability of an ontology as a knowledge representation method to represent fundamental investment strategies. More specifically, we seek to examine whether the characteristics of knowledge reusability, reliability, and intelligibility (by providing shared understanding for interoperability) that are characteristic of knowledge representation methods, may be brought to bear upon fundamental investing. Consequently, our paper illustrates the ability of unifying the strategies' formats which not only enables knowledge sharing among investors on different platforms, but also operationalize those investment strategies.

Our efforts herein go beyond representing the concepts and inter-concept relationships that are descriptive of fundamental investment strategies, as we also demonstrate that ontologies using Semantic Web Rule Language (SWRL) rules can deploy these strategies as stock pickers (also referred to as stock screening). SWRL rules define logics and their consequents such that ontological concepts can be constrained in very specific ways. The following section provides some current finance ontologies. The section following describes our ontology (StratO). Which is evaluated afterwards. The final section provides discussions and conclusion.

Ontologies in Finance

The financial industry clearly recognizes the benefits that ontologies may bring to some of its stakeholders. A prominent example of this is the Financial Industry Business Ontology (FIBO), which is " a modularized formal model of concepts represented by finance industry terms as used in official financial organization documents…" (Object Management Group 2015, p. 5). These concepts are real things in the world of the finance industry and specifically exclude "concepts about the structure of content, messages, information or data, even if that data is in turn about the finance industry" (Object Management Group 2015, p. 10). In other words, FIBO is not suited to our stated goal of developing an ontology that is appropriate for representing and executing fundamental investment strategies. It is not equipped to represent the concepts, relationships and data needed for our purposes. For example, FIBO expressly excludes modeling constructs for financial ratios and financial line items. Without such representations one cannot hope to model an actionable knowledge representation for investment strategies. FIBO, however, can be used to standardize a small subset of the concepts we require for our purposes. We plan to integrate, where possible, our developing ontology with the FIBO conceptual model. It is worth noting that other ontologies have been proposed in finance. These ontologies are much more limited in scope. Generally, they are un-instantiated frameworks. A Financial Securities Ontology is proposed in (Bennett 2007) and represents an attempt to develop a taxonomy of concepts and inter-concept relationships that are descriptive of equities. An ontology for mutual funds is proposed in (Banerjee 2013). This ontology describes the basic functions of a mutual fund at a very high level and is very narrow in scope. A proposal for ontologies designed to support a hypothetical multi-agent system for investment decision support is presented in (Zhang et al. 2000). However, the authors provide very few details about their proposed ontology and prototype. It becomes impossible to judge the contribution therein. Another example is the Financial Report Ontology[1] (FRO) which ontologizes United States Generally Accepted Accounting Principles (US GAAP) and International Financial Reporting Standards (IFRS). This ontology is designed for the representation of financial reports in machine readable format.

While the financial services industry recognizes the potential benefits of ontologies and formal conceptual models in many of its facets, we do not find any work in the academic or practitioner literature that attempts to provide a conceptual framework for popular fundamental investment strategies. In that vein, we also are unable to find work that develops an actionable ontology that can execute such strategies. Top level descriptions of investment concepts fall well short of the mark in this regard.

Popular accounts of fundamental investment strategies abound in the form of books and tutorials. Several automated stock screening platforms incorporating many of these strategies exist. However, these services offer their own idiosyncratic interpretations of these strategies with no clearly defined representation from which to draw. We argue here that there are several potential benefits to developing an ontology that provides the concepts, relationships and axioms necessary to represent and execute these strategies.

[1] http://financialreportontology.wikispaces.com/home

Ontology Design (StratO)

This work employs the Web Ontology Language[2] (OWL2) for describing the high-level constructs in our designed ontology (StratO). Ontology editing is done in Protégé 5 and reasoning is enabled using the highly-optimized Pellet reasoner (Sirin et al. 2007).

The proposed ontology has a primary design objective, the ability to successfully model and operationalize a popular fundamental investment strategy (CANSLIM is the development case). The CANSLIM investment strategy provides individual investors with stock selection recommendations based on guidelines for the stock screening, purchasing, and selling (for details of CANSLIM strategy see Galgani 2013). Our ontology consists of three main concepts - *market conditions*, *traded companies*, and *investment strategy*, since the strategy will evaluate the traded company based on the market conditions. Each of these concepts is presented in the three subsections below.

Market conditions

Market conditions are the dynamic characteristics of the investment environment. The market's characteristics change over time and any investment strategy should take into account their current state. For example, some financial analysts would recommend making a certain type of investment in bull cycles and a different type of investment in bear cycles. More nuance may be introduced, such that a strategy might recommend market entry just before the beginning of a bull cycle, or just before the start of a bear cycle. A bull cycle is a period of market activity characterized by rapidly increasing stock prices. A bear cycle is characterized by rapidly decreasing stock prices. StratO, therefore, must capture, at minimum, some basic facts necessary to describe market conditions through time.

The ontology treats the trading day as the most granular representation of market dynamism. The trading day is simply any day in which stocks are traded and is represented by a `Day` class. The `Day` class is further refined into six subclasses which represent different states descriptive of a trading day as per CANSLIM. `HighVolumeDay` is defined as a day with volume higher than the average trading volume of an index. `DistributionDay` is a day where major stock indices close lower on very high volume. `DownTrendDay` is a day where it has been determined that the market has begun a move towards bearish conditions. `NewLowDay` is a day where a major index closes at a new low for a given market cycle. A `RallyDay` is a day after the market has `bottomed` (i.e. reached a new low) where the market closes higher than the previous trading day. A `FollowThroughDay` confirms the rally to be a sign that the market is moving from a bear cycle into a bull cycle.

Classes	
`Day`	Represents a generic Day during which stock is traded in major indices.
`DistributionDay`	A Day where major stock indices close lower on very high volume.
`HighVolumeDay`	A Day with volume higher than the average trading volume of an index.
`DownTrendDay`	A Day where it has been determined that the market has begun a move towards bearish conditions.
`FollowThroughDay`	A Day that serves as confirmation that a rally is indeed signaling that the market is moving from a bear cycle into a bull cycle.
`NewLowDay`	A Day where a major index closes at a new low for a given market cycle.
`RallyDay`	Is a Day after the market has "bottomed" (i.e. reached a new low) where the market closes higher than the previous trading day
`Week`	Represents a collection of Days into a calendar Week.
`DownWeek`	A Week that is characterized by bearish market conditions.
`UpWeek`	A Week that is characterized by bullish market conditions.
`Quarter`	A quarter of a year
`Year`	A year

Table 1. Market Condition Classes (indentation denotes class hierarchy)

The `Day` class and its subclasses are instantiated with individuals (an individual is an instance of a class) that represent actual trading days. The characteristics of each trading day and its relationships with other

[2] http://www.w3.org/TR/owl2-overview/

trading days and the market context determine the *kind* of `Day` an individual belongs to. Accordingly, instances of the `Day` class are interrelated by a series of binary predicates. Further, Days are collected into Weeks, Weeks into Months, Months into Quarters and Quarters into Years (see Table 1). Each aggregation is represented by a corresponding class, individuals of which correspond to real weeks, months, quarters and years. Relations are created to capture the relative temporal positioning of the individuals of these classes. For example, the binary predicate hasPreviousWeek(w_t,w_{t-n}) describes the relative temporal positioning of two Week individuals w_t, and w_{t-n}, such that *t* is a point in time and *n* is some number of time intervals. Additional properties are defined to further refine this predicate such as `hasPreviousWeek1` which is used to denote that a Week individual has as its immediate prior week, some other Week individual. This technique is used for Day individuals. Domain and range for these properties are not set so that hasPreviousWeek(d,w) is possible where *d* is a Day individual and *w* is a week individual.

The `Week` class has two subclasses, `DownWeek` and `UpWeek`. `DownWeek` is used to denote those weeks which occur during a bear cycle, and `UpWeek` is used to denote those weeks which occur during a bull cycle. The days contained within a week determine whether a week is UpWeek or DownWeek. Tables 2 - 4 below summarize the properties and axioms used to model market conditions.

Object Properties	
`hasDay`	Relates any relevant individual to an instance of Day hasDay(Week, Day).
`hasPreviousDay`	Relates two Days such that one ambiguously (temporal distance is not specified) precedes the other.
`hasPreviousDay1`	Relates two Days such that one precedes the other by a single Day.
`hasWeek`	Relates any relevant individual to a Week, e.g. hasWeek(Day, Week).
`hasPreviousWeek`	Relates two individuals (either a Day or a Week) such that a Day or a Week temporally proceeds a Week by an ambiguously defined temporal distance.
`hasPreviousWeek1`	Relates two individuals (either a Day or a Week) such that a Day or a Week temporally proceeds a Week by exactly one week.
`hasQuarter (1,2,3,4)`	hasQuarter and its variants hasQuarter1, hasQuarter2, hasQuarter3, hasQuarter4 relate an individual to a Quarter. Where that individual is a Year, it may have hasQuarter1, hasQuarter2, hasQuarter3, and hasQuarter4 relations with a Quarter to denote the first, second, third and fourth quarters of a year. This property also relates FirmIndicators (to be discussed later) to a Quarter.
`hasYear`	Relates Day, Quarter, and Week individuals to a Year. This property also relates FirmIndicators (to be discussed later) to a Year.

Table 2. Market Condition Object Properties

Data Properties	
`hasVolume`	An integer represents the volume of stock traded on a given index.
`hasClose`	The percentage change on an index at the end of trading on a given Day.
`hasCloseValue`	The value on which an index closed at the end of trading on a given Day.

Table 3. Market Condition Data Properties

Axioms	
Day(?d), hasPreviousDay1(?d, ?d1), hasClose(?d, ?c), hasVolume(?d, ?v), hasVolume(?d1, ?v1), greaterThan(?v, ?v1), lessThanOrEqual(?c, "-0.02"^^decimal) -> DistributionDay(?d)	Determines the membership of a Day individual vis-à-vis the CANSLIM inspired DistributionDay class. Days that close lower on higher volume that their immediately prior Day are distribution days.
DownWeek(?prevWeek), Week(?w), (hasDay exactly 0 FollowThroughDay)(?w), hasPreviousWeek1(?w, ?prevWeek) -> DownWeek(?w)	A Week that follows a DownWeek is also a DownWeek given that it contains no FollowThroughDay days.

DownTrendDay(?d), Week(?w), hasDay(?w, ?d) -> DownWeek(?w)	Any Week individual which has as one of its hasDay ranges a DownTrendDay is a DownWeek.
Week(?w), (hasDay min 1 FollowThroughDay)(?w) -> UpWeek(?w)	Any Week individual which has as one of its hasDay ranges at least one FollowThroughDay is an UpWeek
Day(?d), DownWeek(?w), Index(?i), hasPreviousDay1(?d, ?pd1), hasWeek(?d, ?w), hasCloseValue(?d, ?cv), hasCloseValue(?pd1, ?pd1cv), hasLow(?i, ?low), lessThan(?cv, ?low), lessThan(?cv, ?pd1cv) -> NewLowDay(?d)	Any Day, occurring in a DownWeek, which hasCloseValue less than the lowest close value of its relevant index and closes lower than its immediately prior trading Day is a NewLowDay.
Day(?d), Index(?i), hasAverageVolume(?i, ?av), hasVolume(?d, ?v), greaterThan(?v, ?av) -> HighVolumeDay(?d)	A Day with higher than average trading volume is a HighVolumeDay
Day(?d), DownWeek(?w1), RallyDay(?d1), hasPreviousDay1(?d, ?d1), hasPreviousWeek1(?w, ?w1), hasWeek(?d, ?w), hasCloseValue(?d, ?cv), hasCloseValue(?d1, ?cv1), greaterThan(?cv, ?cv1) -> FollowThroughDay(?d)	A FollowThroughDay is Day which occurs during a DownWeek, follows a Day in a previous Week which is a RallyDay and closes higher than its previous Day.
Day(?d), (hasPreviousDay min 3 DistributionDay)(?d), (hasPreviousWeek min 3 UpWeek)(?d) -> DownTrendDay(?d)	A DownTrendDay is a Day which follows three DistributionDays occurring in a three week period.
Day(?d), HighVolumeDay(?d), NewLowDay(?nld), hasPreviousDay(?d, ?nld), hasPreviousDay1(?d, ?d1), hasCloseValue(?d, ?CurrClose), hasCloseValue(?d1, ?PrevClose), greaterThan(?CurrClose, ?PrevClose) -> RallyDay(?d)	A RallyDay is a HighVolumeDay that follows the establishment of a new low for a given index. A RallyDay must close higher than the Day it immediately proceeds.

Table 4. Market Condition Axioms (SWRL Rules)

Traded Companies

Traded companies are described by a number of classes, properties and axioms (see tables 5-7). As StratO is designed to model the CANSLIM strategy, it must be equipped with the concepts needed to capture the fundamental condition of the individuals which underlie traded companies. These concepts are subclasses of the `FirmIndicator` class. StratO accounts for changes in the fundamentals of the traded company this by reusing components of the market condition module. For example, CANSLIM requires that stocks which are candidates for purchase have quarterly EPS growth of at 25% in recent quarters (Galgani 2013) So, not only is it necessary to capture relevant fundamental indicators, it is also necessary to capture the moments in time to which the indicators refer.

Classes	
`FirmIndicator`	This is the root class to which all fundamental indicators belong. This table contains only two of the 15 fundamental indicators included in the ontology.
`EPS`	Earnings per Share, an all-important fundamental indicator that represents returns to shareholders for each earnings period.
`AnnualEPS`	Earnings per Share on an annual basis.
`QuarterlyEPS`	Earnings per Share on a quarterly basis.
`NetSales`	Total revenue net of discounts.
`AnnualNetSales`	Net Sales on an annual basis.
`QuarterlyNetSales`	Net Sales on a quarterly basis.
`Firm`	The collection of traded companies to be analyzed for investment viability.

Table 5. Traded Company Classes

Object Properties	
`hasFirmIndicator`	A Firm may have several indicators. These indicators are instances of various fundamental indicators
`hasEPS`	Firms can be associated with several instances of the EPS class (or any subclass of the FirmIndicator class). The hasEPS property may have as its range any EPS individual.
`hasNetSales`	Firms can be associated with several instances of the NetSales class (or any subclass of the FirmIndicator class). The hasNetSales property may has as its range any NetSales individual.
`hasQuarter`	An individual of any FirmIndicator type must be associated with at least one reporting Quarter. Annual indicators (e.g. AnnualEPS) must be associated with four quarters belonging to the relevant reporting Year.
`hasYear`	An individual of any FirmIndicator type must be associated with one and only one year. The relevant Year for quarterly indicators is inferred based on their associated Quarter.

Table 6. Traded Company Object Properties

Data Properties	
`hasTicker`	At the moment, this is the only data property associated with Firm individuals. It uses the standard EDGAR ticker literal (a unique identifier) as its range. Its domain is the Firm
`hasValue`	The hasValue data property has the domain FirmIndicator. All instances of a FirmIndicator type must have a corresponding hasValue property. The range of hasValue for QuarterlyEPS, for example, may be "2.3"^^Decimal.

Table 7. Traded Company Data Properties

Investment Strategies

At this point it is necessary to introduce the hitherto unexplored `Request` class. The `Request` class is a collection of individuals each of which captures a single traded company in a user's query. A Request individual must have two object property assertions along the properties `hasFirm` and `hasDay`. The ranges of these property assertions are `Firm` and `Day` classes respectively. The Day individual associated with a Request individual indicates the user's desired investment date. The Firm individual associated with a Request individual indicates the firm about which a user is seeking investment justification.

CANSLIM is primarily modeled via SWRL rules (see Table 8). The two strategy classes, which respectively are subclasses of the `Firm` and `Request` classes, are collections of Firm and Request individuals which meet the requirements of the relevant strategy. A subclass of the `Firm` class is always CANSLIM with a *context free recommendation*. Its individuals are Firm individuals, the classification of which follows from investment rules regarding the nature of a traded company's fundamentals alone. A subclass of the `Request` class is always CANSLIM with a *context aware recommendation*. Its individuals are Request individuals, the classification of which follows from: (1) the classification of the Firm associated with the Request into a *context free recommendation* and (2) the appropriateness of market conditions for investment, inferred from the Day individual associated with the Request individual. The SWRL rules associated with these classifications are given in Table 9.

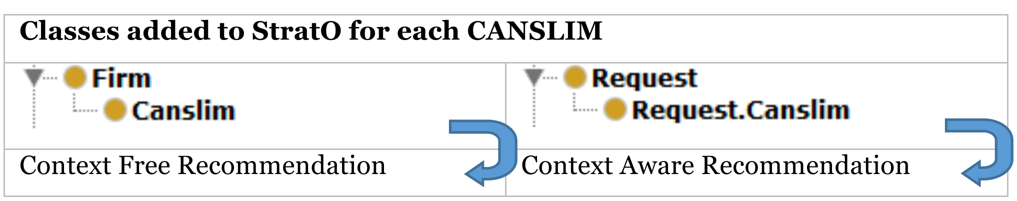

Figure 1. Classes Added to StratO for CANSLIM

CANSLIM SWRL Rules	
Firm(?f), QuarterlyEPS(?qe), QuarterlyNetSales(?qns), hasEPS(?f, ?qe), hasNetSales(?f, ?qns), hasROE(?f, ?r), hasYear(?qe, Year2), hasYear(?qns, Year2), hasChange(?qe, ?qec), hasChange(?qns, ?qnsc), hasValue(?r, ?rv), greaterThan(?rv, "17"^^int), greaterThanOrEqual(?qec, "25"^^int), greaterThanOrEqual(?qnsc, "25"^^int) -> Canslim(?f)	A context free recommendation is evaluated. This rule implements a subset of the CANSLIM recommendations (see Figure 4) such that a context free recommendation for the CANSLIM strategy is issued for Firm individuals that: have 25% growth in quarterly EPS and Net Sales, and return on equity (ROE) of at least 17%.
Canslim(?f), Request(?r), UpWeek(?w), hasDay(?r, ?d), hasFirm(?r, ?f), hasWeek(?d, ?w) -> Request.Canslim(?r)	A context aware recommendation is evaluated. This recommendation follows the CANSLIM principle of investing when the market is in a bull cycle. To that end, market conditions are evaluated, and the Firm associated with the Request is checked for a context free recommendation.

Table 8. CANSLIM SWRL Rules

Evaluation

The evaluation of a design demonstrates the extent to which it meets its stated objective. As the objective of StratO is to demonstrate that a minimal ontology (i.e. large number of reusable components) can be used to both represent and operationalize popular investment strategies, the ontology will be evaluated by demonstrating its ability to model CANSLIM without structural changes. To do so, a case is prepared involving a single hypothetical firm and the strategy (see Table 9). The table presents a hypothetical firm's fundamentals over a period of two years (2015 and 2016). The first row of each section is populated with annual data where possible. The remaining four rows of each section are dedicated to quarterly data. For example, annual EPS in 2015 is $6.30 while third quarter EPS is $1.70.

Year	Quarter	Firm	Net Sales	EPS	%Change Net Sales	%Change EPS	ROE
2015	NA	Firm1	$ 21,000,000,000	$ 6.30			27%
2015	1st	Firm1	$ 7,000,000,000	$ 1.80			
2015	2nd	Firm1	$ 4,000,000,000	$ 1.60			
2015	3rd	Firm1	$ 6,000,000,000	$ 1.70			
2015	4th	Firm1	$ 4,000,000,000	$ 1.20			
2016	NA	Firm1	$ 29,000,000,000	$ 7.80	28%	19%	32%
2016	1st	Firm1	$ 8,800,000,000	$ 2.10	20%	14%	
2016	2nd	Firm1	$ 6,000,000,000	$ 1.90	33%	16%	
2016	3rd	Firm1	$ 7,900,000,000	$ 2.20	24%	23%	
2016	4th	Firm1	$ 6,300,000,000	$ 1.60	37%	25%	

Table 9. Firm1 Fundamental Data

Week	Day	Close %	Close Value	Trading Volume
Week01	Day1	-0.01	16003	11,250,000
Week01	Day2	-0.02	15990	12,200,000
Week01	Day3	0.03	16005	13,000,000
Week01	Day4	-0.01	16000	11,950,000
Week01	Day5	-0.03	15990	12,000,000
Week01	Day6	0.02	16309.8	12,100,000
Week02	Day7	0.01	16472.9	12,300,000
Week02	Day8	-0.03	15978.7	14,000,000
Week02	Day9	0.01	16138.5	11,000,000
Week02	Day10	-0.012	15944.8	10,900,000
Week02	Day11	0.02	16263.7	12,000,000
Week02	Day12	0.001	16280.0	13,000,000
Week02	Day13	0.002	16312.6	12,500,000
Week03	Day14	0.012	16508.3	12,300,000
Week03	Day15	-0.0021	16473.6	12,000,000
Week03	Day16	-0.024	16078.3	13,500,000
Week03	Day17	-0.002	16046.1	13,000,000
Week03	Day18	0.002	16078.2	12,300,000
Week03	Day19	-0.01	15917.4	12,200,000
Week03	Day20	0.002	15949.3	13,200,000
Week04	Day21	0.005	16029.0	14,100,000
Week04	Day22	-0.034	15484.0	15,100,000
Week04	Day23	-0.04	14864.7	16,000,000
Week04	Day24	-0.02	14567.4	15,000,000
Week04	Day25	-0.012	14392.6	13,200,000
Week04	Day26	0.013	14579.7	14,000,000
Week05	Day27	0.02	14871.3	13,500,000

Table 10. Market Data

Data in Table 9 is manually imported into StratO. The first step is to create an instance of the Firm class to correspond to the hypothetical Firm1. The Firm1 individual is associated with a data property, `hasTicker` that is set to the literal "FIIRRM." Next, individuals corresponding to each the fundamental data in Table 9 are generated. For example, an instance of the EPS class is created for each EPS figure reported. An annual EPS figure, for example, has four object properties corresponding to each of the four quarters of the year it captures. Figure 2 below illustrates the representation of Table 9 data in StratO concepts.

Market condition data is also simulated (see Table 10). The representation of these trading days in StratO is illustrated in Figure 3. Based on the simulated Day individuals and market condition axioms, the model reasoned is able to classify a day into zero or more of the 6 Day subclasses. Figure 3 also illustrates the classification of Day individuals. The type assertions circled in red in are the inferences made based on StratO axioms about the hypothetical "Day 26." So, "Day26" is simultaneously a `DownTrendDay`, a `HighVolumeDay`, and a `RallyDay`.

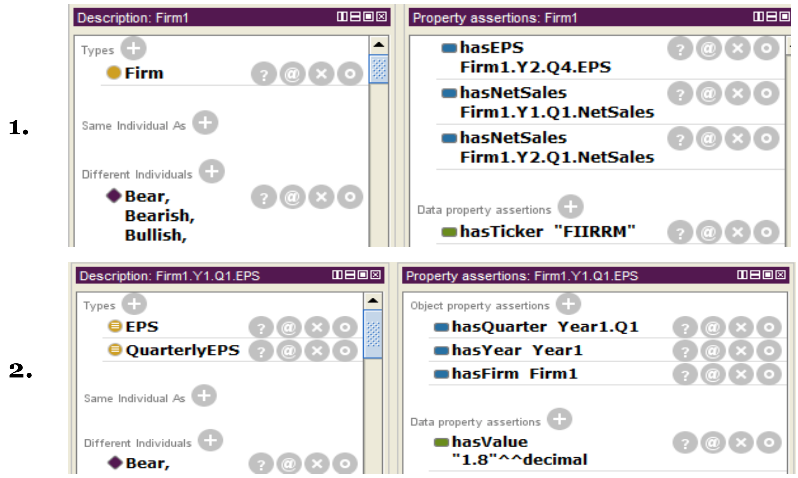

Figure 2. Fundamental Firm Data Representation in StratO

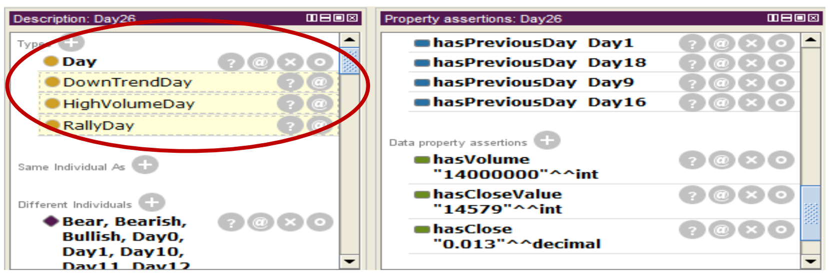

Figure 3. Day26 Inference

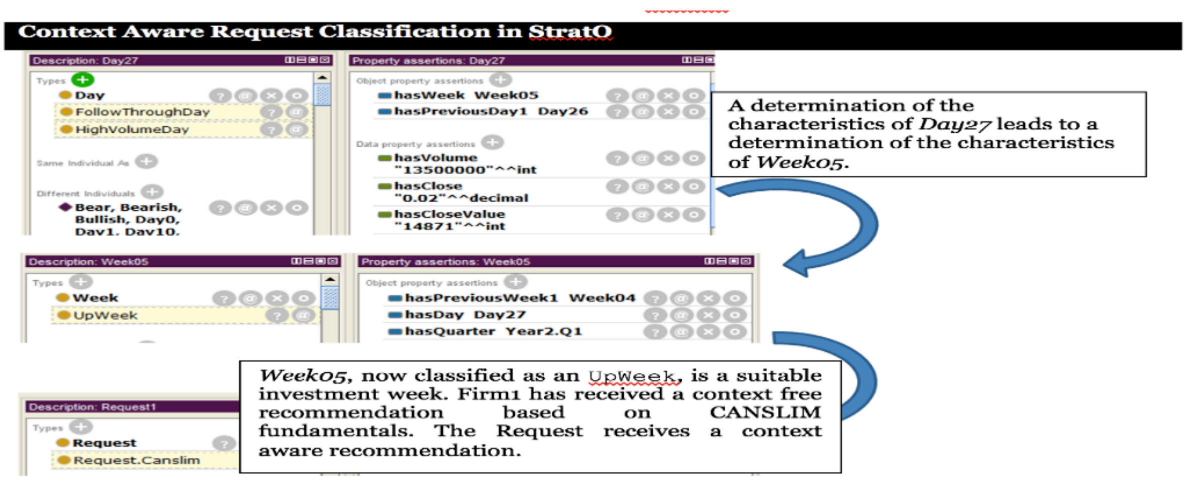

Figure 4. Final Request Classification

A request individual is created by a hypothetical user. The users desired investment date is “Day27,” and would like to know if investing using the CANSLIM strategy would support making an investment on that Day. A Request individual is created to represent this information. Firm1, prior to the generation of the request individual has received a context free recommendation that this day would be a good day to invest using the CANSLIM strategy (see Figure 4). *Day27* is checked to determine if it is a suitable day for investing (i.e. if it occurs during a bull cycle). To make this determination, it is reasoned whether *Day27* occurs during a `DownWeek` or during an `UpWeek`. If it occurs during an `UpWeek`, it is a suitable investment day. Figure 7 illustrates the inference that has occurred to make these determinations. After this occurs, then an investment will be made completing the Investment Support Decision Model.

Conclusion and Future Work

StratO strategy modeling is designed such that ultimately multiple strategies may be modelled without changing the classes and properties associated with market conditions and traded companies. This represents the goal of creating a standardized knowledge representation that can be reusable is a standard format. The work presented in this paper provides preliminary evidence that ontologies are suited to the task of modeling and executing financial investment strategies. This finding is substantial especially in light of the fact that the standardization and reusability benefits of ontologies can be brought to bear upon the rather fragmented popular representations and implementations of fundamental strategies. There currently exist no ontologies in the finance literature specifically intended to model fundamental investment strategies, let alone ontologies that can act upon their representations of fundamental investment strategies. In this paper we showed that SWRL rules are sufficiently expressive to mobilize fundamental investment strategies expressed in an ontology language. While certain aspects of SWRL that could have been very useful to us are still under development (e.g. rule atoms that provide decidability on dates and other temporal ontology assertions), we have been able to define a prototype with its existing atoms. We closely follow the development of semantic web technologies and hope to reformulate our ontology as more expressivity is introduced to ontology languages. Another limitation is that we have only used simulated data for a single firm in this exposition. We are working on automatically populating the ontology with a corpus of current, real-world, firm and market data. An important goal of this project is to show that an ontology is capable of both representing and executing popular fundamental investment strategies. We developed our ontology using the CANSLIM fundamental investment strategy and demonstrate that the representation is imbued with the semantics necessary to actually execute the CANSLIM strategy. The development of this initial prototype ontology presents many vistas of opportunity for future work. We hope to vastly expand the number of strategies that we represent and execute using this ontology. We intend to integrate the relevant components of this ontology with the FIBO top level ontology. Further, we want to test the ontology on the entire population of firm equities traded on the New York Stock Exchange (NYSE). That is, for each strategy represented in StratO, we want to collect its recommendations across several market contexts (acquired by backtesting). Our future work will evaluate our efforts along those lines by examining the stock selection recommendations provided by online stock screening platforms, comparing these with the recommendations provided by StratO on the same investment strategies. The actionability of StratO simultaneously serves to provide additional utility in StratO while validating the completeness and richness of our representations.

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