# Beeld en Geluid

- Lorem ipsum dolor sit amet
- Consectetur adipisicing elit
- Sed do eiusmod tempor incididunt ut labore
- Et dolore magna aliqua

# Hooked on Music

John Ashley Burgoyne

Music Cognition Group
Institute for Logic, Language and Computation
University of Amsterdam

# Hooked on Music

John Ashley Burgoyne · Jan Van Balen
Dimitrios Bountouridis · Daniel Müllensiefen
Frans Wiering · Remco C. Veltkamp · Henkjan Honing

and thanks to

Fleur Bouwer · Maarten Brinkerink · Aline Honingh · Berit Janssen · Richard Jong
Themistoklis Karavellas · Vincent Koops · Laura Koppenburg · Leendert van Maanen
Han van der Maas · Tobin May · Jaap Murre · Marieke Navin · Erinma Ochu
Johan Oomen · Carlos Vaquero · Bastiaan van der Weij

# ‘Henry’

Dan Cohen & Michael Rossato-Bennett · 2014 · *Alive Inside*

# Long-term Musical Salience

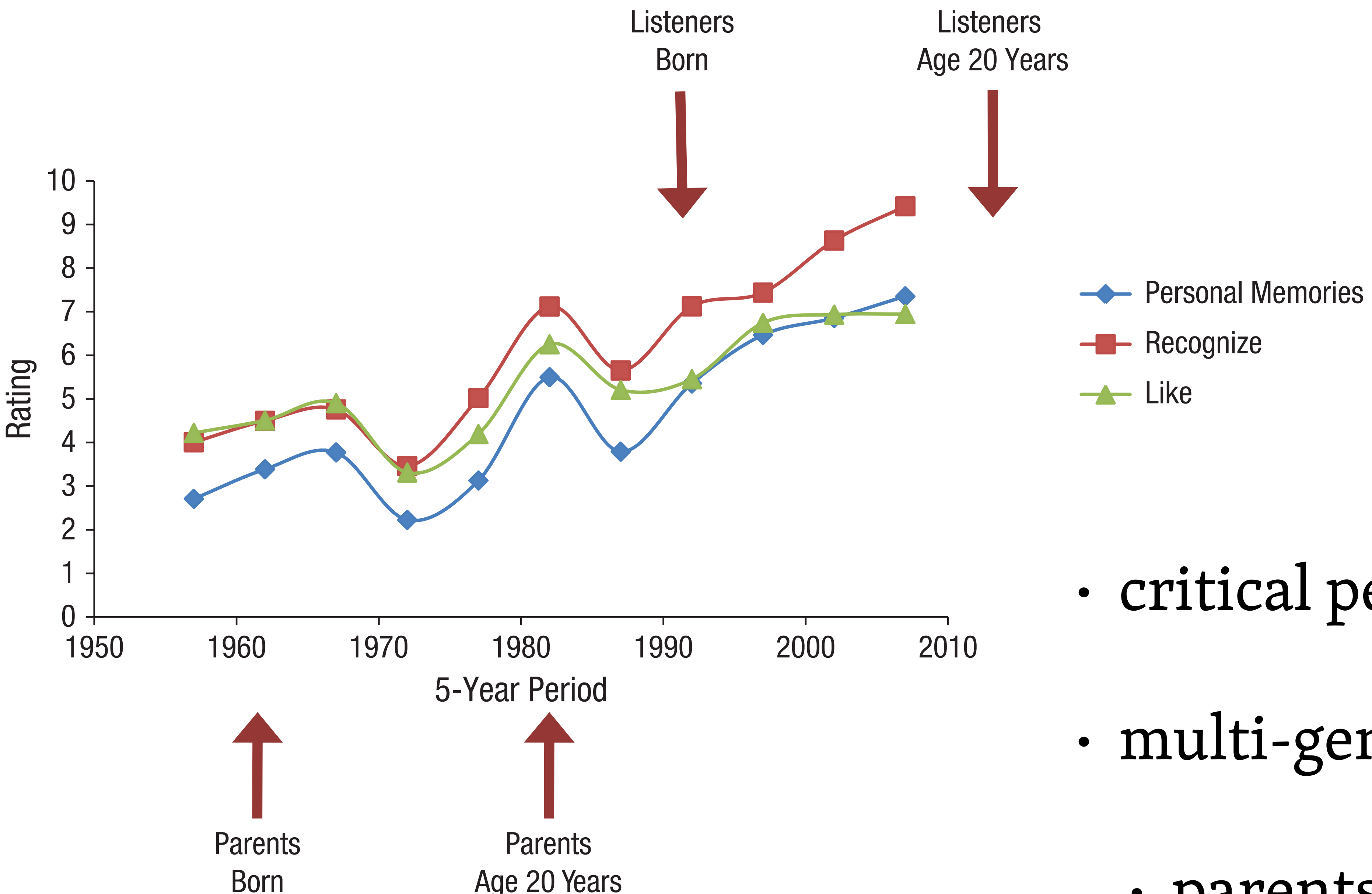
**salience** · the absolute 'noticeability' of something

- cf. *distinctiveness* (relative salience)

**musical** · what makes a bit of music stand out

**long-term** · what makes a bit of music stand out so much that it remains stored in long-term memory

# Reminiscence Bumps




- critical period ages 15–25
- multi-generational
  - parents *and* grandparents

C. Krumhansl & J. Zupnick · 2013 · Cascading Reminiscence Bumps in Popular Music

# Explicit vs. Implicit Memory

- short-term memory
- two sets of melodies
- some repeated
- Q: ’old’ or ‘new’?
- contradiction between explicit/implicit memory


THE ROLE OF FEATURES AND CONTEXT IN RECOGNITION OF NOVEL MELODIES

DANIEL MÜLLENSIEFEN
*Goldsmiths, University of London, London, United Kingdom*

ANDREA R. HALPERN
*Bucknell University*

**WE INVESTIGATED HOW WELL STRUCTURAL FEATURES** such as note density or the relative number of changes in the melodic contour could predict success in implicit and explicit memory for unfamiliar melodies. We also analyzed which features are more likely to elicit increasingly confident judgments of “old” in a recognition memory task. An automated analysis program computed structural aspects of melodies, both independent of any context, and also with reference to the other melodies in the testset and the parent corpus of pop music. A few features predicted success in both memory tasks, which points to a shared memory component. However, motivic complexity compared to a large corpus of pop music had different effects on explicit and implicit memory. We also found that just a few features are associated with different rates of “old” judgments, whether the items were old or new. Rarer motives relative to the testset predicted hits and rarer motives relative to the corpus predicted false alarms. This data-driven analysis provides further support for both shared and separable mechanisms in implicit and explicit memory retrieval, as well as the role of distinctiveness in true and false judgments of familiarity.

*Received: February 2, 2013, accepted September 21, 2013.*

**Key words:** implicit vs. explicit memory, computational modeling, automatic music analysis, true and false memories, distinctiveness

REMEMBERING MUSIC IS AN IMPORTANT PART of many people’s lives, no matter what their musical background. In some ways, we have excellent memory for music. People maintain a large corpus of familiar tunes in their semantic memory. The representations are accurate in that someone can typically say if there is a wrong note in a familiar tune (Dowling, Bartlett, Halpern, & Andrews, 2008) and memory for tunes seems to last over one’s lifetime (Bartlett & Snelus, 1981). On the other hand, encoding of new music is quite difficult (Halpern & Bartlett, 2010). Sometimes a tune sounds familiar but it turns out that it is only similar to one we knew in the past, creating false alarms. And people who have bought or downloaded some music only to discover the piece already in their collection have experienced the other kind of error, a miss.

Explaining success and failures in memory for music by applying well-understood memory principles has not always been successful, which raises the question of whether memory for music is special or different from memory for other kinds of information. For instance, type of encoding task seems not to affect overall recognition performance for unfamiliar tunes (Halpern & Müllensiefen, 2008; Peretz, Gaudreau, & Bonnel, 1998) and musical expertise does not always increase this sort of recognition memory (Demorest, Morrison, Beken, & Jungbluth, 2008; Halpern, Bartlett, & Dowling, 1995). However, in common with other materials, familiar tunes are generally recognized more accurately than unfamiliar tunes (Bartlett, Halpern, & Dowling, 1995). These predictors are largely concerned with the encoding situation, state of the rememberer, and some general aspects of the to-be-remembered items.

In contrast, our goal in this paper is to examine the extent to which two other factors can predict memorability of, in this case, real but unfamiliar pop tunes. One factor is the *features* of the tunes themselves. We take advantage of powerful statistical modeling techniques as well as automated feature extraction software to allow simultaneous evaluation of many features at the same time.

This discovery-driven approach assumes that stimuli in the world are composed of many kinds of features, and that people can employ statistical learning to encode those features. People certainly employ statistical learning in procedural tasks, like learning artificial grammars (Pelucchi, Hay, & Saffran, 2009) and motor sequences (Daselaar, Rombouts, Veltman, Raaijmakers, & Jonker, 2003), regardless of whether the features are processed consciously or not. The feature approach is well established in memory research. For example, Cortese, Khanna, and Hacker (2010) looked at recognition memory for over 2500 monosyllabic words, taking as

*Music Perception,* VOLUME 31, ISSUE 5, PP. 418–435, ISSN 0730-7829, ELECTRONIC ISSN 1533-8312.  DOI: 10.1525/MP.2014.31.5.418

D. Müllensiefen & A. Halpern · 2014 · The Role of Features in Context

# ‘Plinks’

- trivia challenge
- 28 top songs ‘of all time’
- 400-ms music clips
- student participants
- 25-percent identification rate for artist and title



PLINK: “THIN SLICES” OF MUSIC

CAROL L. KRUMHANSL
*Cornell University*

SHORT CLIPS (300 AND 400 MS), TAKEN FROM POPULAR songs from the 1960’s through the 2000’s, were presented to participants in two experiments to study the detail and contents of musical memory. For 400 ms clips, participants identified both artist and title on more than 25% of the trials. Very accurate confidence ratings showed that this knowledge was recalled consciously. Performance was somewhat higher if the clip contained a word or part-word from the title. Even when a clip was not identified, it conveyed information about emotional content, style and, to some extent, decade of release. Performance on song identification was markedly lower for 300 ms clips, although participants still gave consistent emotion and style judgments, and fairly accurate judgments of decade of release. The decade of release had no effect on identification, emotion consistency, or style consistency. However, older songs were preferred, suggesting that the availability of recorded music alters the pattern of preferences previously assumed to be established during adolescence and early adulthood. Taken together, the results point to extraordinary abilities to identify music based on highly reduced information.

*Received August 3, 2009, accepted January 3, 2010.*

**Key words:** music memory, meta-memory, popular music, emotion, style

THE CAR RADIO SCANS FROM STATION TO STATION and you recognize a song from decades ago. The title, artist, and lyrics flood into consciousness; perhaps the album cover, the appearance of the artist, or a personal anecdote. Or, if you don’t recognize the song, you might immediately recall its era, musical genre, emotional content, how you danced to it, or its social significance. How detailed are these memories? What attributes of songs can be recalled? How is musical memory organized and which attributes are recalled even if the song is not recognized? And, what is the relationship between musical preferences and other aspects of musical memory? These questions were addressed in two experiments by presenting listeners with short (300 and 400 ms) clips from popular songs. In order to study effects of release date, the songs were taken from the 1960’s through the 2000’s. Listeners were asked to name the artist and title and indicate their confidence in the identifications. They were also asked about the decade of release, and judged the emotional content and style of the songs. After this, listeners were presented with long (15 s) clips for ratings of recognition and liking. They also judged these long clips for emotional content and style, which can be compared with those responses for the short clips as a way of assessing emotion and style consistency.

These questions about musical memory seem obvious, but surprisingly little research has been done on them despite the remarkable expansion of psychological research on music in the last few decades. Perhaps this is because the primary emphasis has been on the cognition of more abstract properties of musical structure (particularly scale, harmony, and meter), with many experiments using materials composed for that purpose and/or presented in timbre-neutral sounds (such as piano). As an example, take a typical study on whether listeners have knowledge of the structure of the major scale. Melodies would be composed for the experiment that conform to the scale and the way tones are typically sequenced in a major key. On a trial one melody would be presented, and then a second melody with one or more tones changed to tones outside the scale. The task is to detect the changed tone(s) and if it is done correctly (as it would be for both musicians and nonmusicians) it is concluded that listeners know the structure of the scale. The findings of a large number of studies demonstrate that these abstract descriptors of musical structure are useful not only in the technical analysis of music, but that they also function as cognitive frameworks for perceiving, remembering, and performing music. Thus, they have cognitive reality. However, these studies do not bear on the long-term effects of sustained exposure to recorded music, which offers a unique opportunity to study human memory.

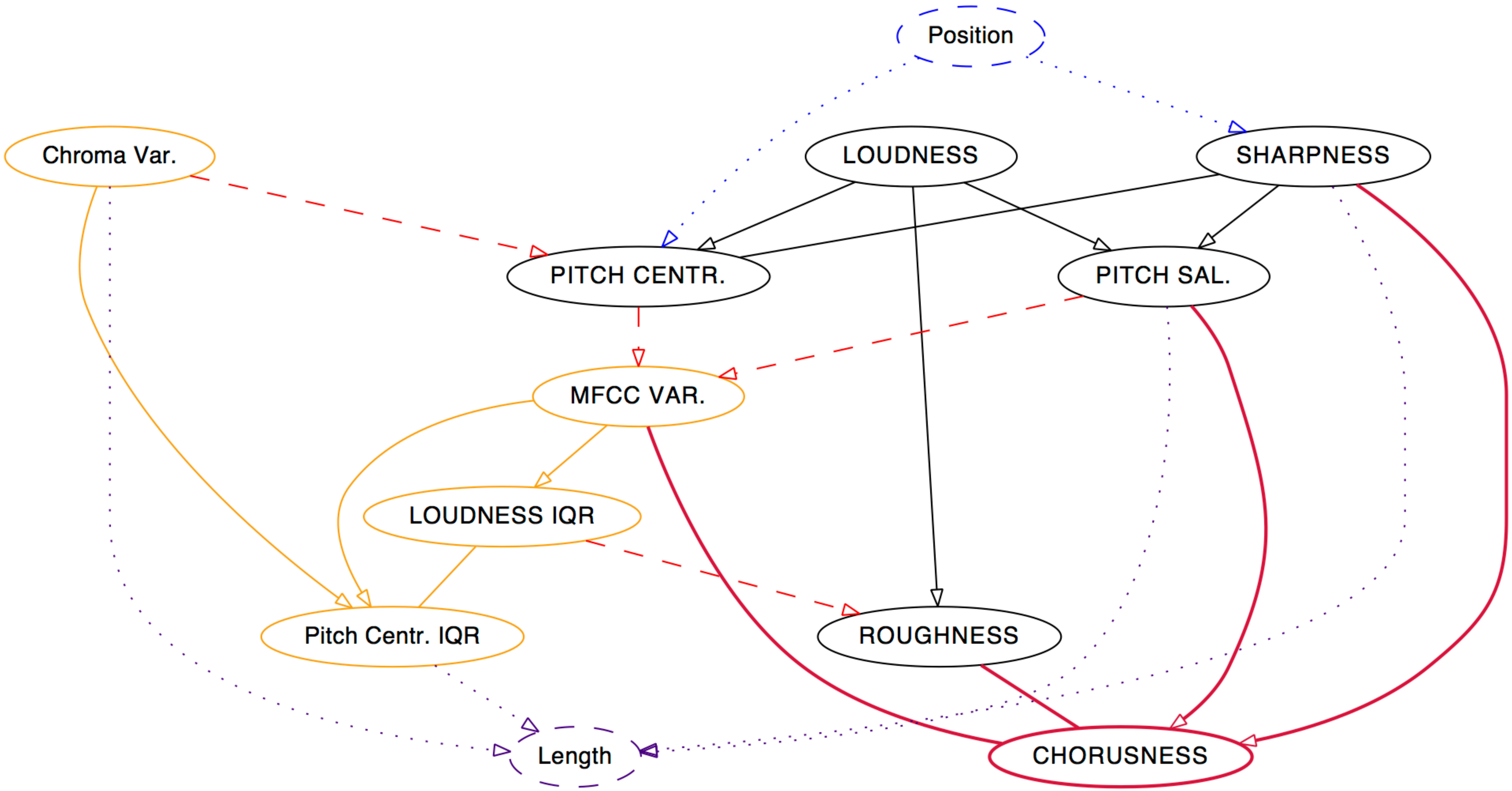
There were three starting points for this study. The first is the concept of “thin slices” made well known by Gladwell’s (2005) *Blink*, from which the title derives. Gladwell describes interesting cases in which, despite very reduced information, experts are able to do such things as judge authenticity of art, predict double faults in tennis, and

*Music Perception* VOLUME 27, ISSUE 5, PP. 337–354, ISSN 0730-7829, ELECTRONIC ISSN 1533-8312  DOI:10.1525/MP.2010.27.5.337



Carol Krumhansl · 2010 · Plink: ‘Thin Slices’ of Music

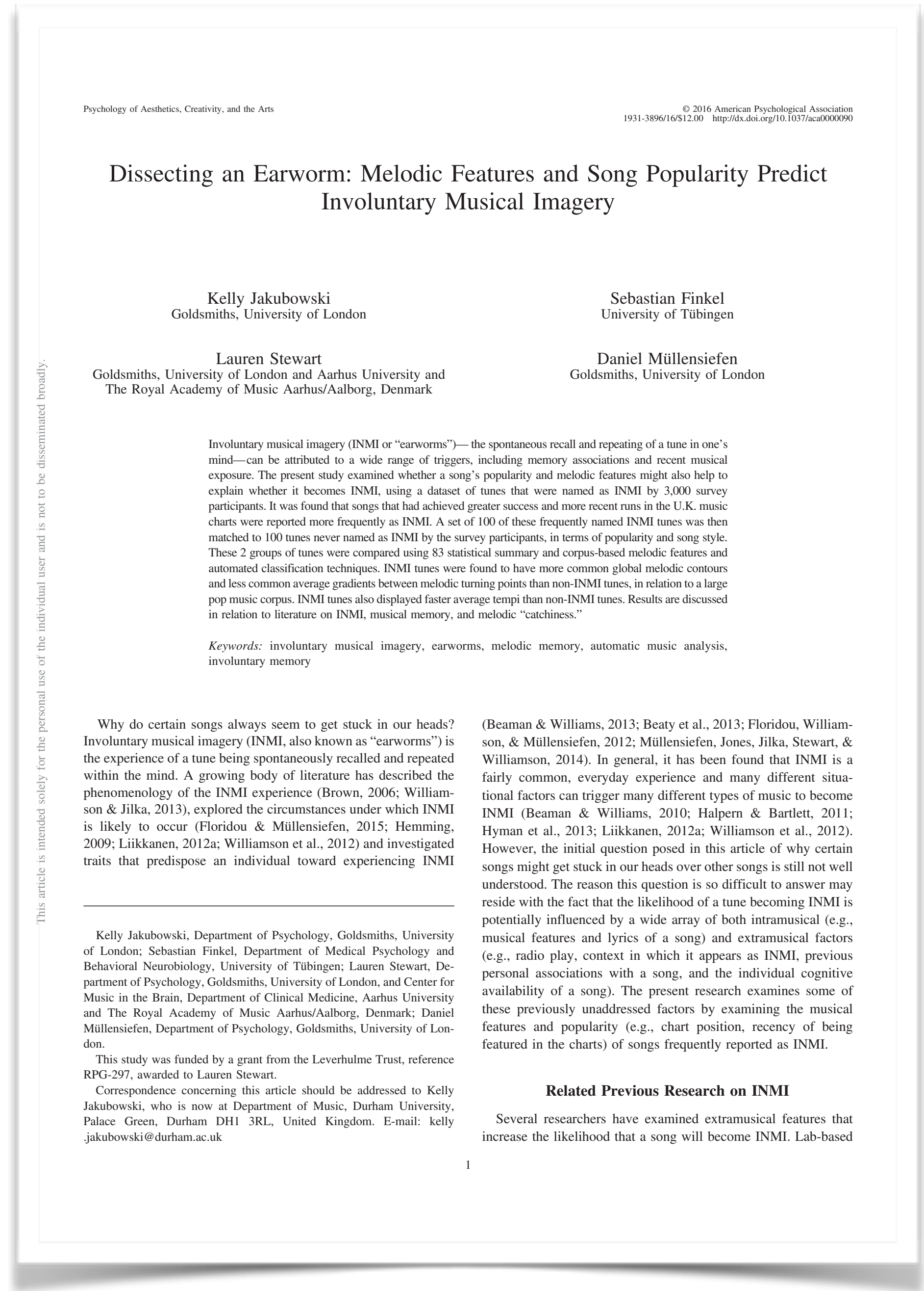
# ‘Chorusness’




J. Van Balen, J. A. Burgoyne, et al. · 2013 · An Analysis of Chorus Features in Popular Song

# Earworms

- 3000 participants (UK)
- popularity
- recency
- melodic contour
- tempo (faster)


Psychology of Aesthetics, Creativity, and the Arts

1931-3896/16/$12.00 http://dx.doi.org/10.1037/aca0000090

## Dissecting an Earworm: Melodic Features and Song Popularity Predict Involuntary Musical Imagery

Kelly Jakubowski
Goldsmiths, University of London

Sebastian Finkel
University of Tübingen

Lauren Stewart
Goldsmiths, University of London and Aarhus University and The Royal Academy of Music Aarhus/Aalborg, Denmark

Daniel Müllensiefen
Goldsmiths, University of London

Involuntary musical imagery (INMI or "earworms")— the spontaneous recall and repeating of a tune in one's mind—can be attributed to a wide range of triggers, including memory associations and recent musical exposure. The present study examined whether a song's popularity and melodic features might also help to explain whether it becomes INMI, using a dataset of tunes that were named as INMI by 3,000 survey participants. It was found that songs that had achieved greater success and more recent runs in the U.K. music charts were reported more frequently as INMI. A set of 100 of these frequently named INMI tunes was then matched to 100 tunes never named as INMI by the survey participants, in terms of popularity and song style. These 2 groups of tunes were compared using 83 statistical summary and corpus-based melodic features and automated classification techniques. INMI tunes were found to have more common global melodic contours and less common average gradients between melodic turning points than non-INMI tunes, in relation to a large pop music corpus. INMI tunes also displayed faster average tempi than non-INMI tunes. Results are discussed in relation to literature on INMI, musical memory, and melodic "catchiness."

*Keywords:* involuntary musical imagery, earworms, melodic memory, automatic music analysis, involuntary memory



Why do certain songs always seem to get stuck in our heads? Involuntary musical imagery (INMI, also known as "earworms") is the experience of a tune being spontaneously recalled and repeated within the mind. A growing body of literature has described the phenomenology of the INMI experience (Brown, 2006; Williamson & Jilka, 2013), explored the circumstances under which INMI is likely to occur (Floridou & Müllensiefen, 2015; Hemming, 2009; Liikkanen, 2012a; Williamson et al., 2012) and investigated traits that predispose an individual toward experiencing INMI (Beaman & Williams, 2013; Beaty et al., 2013; Floridou, Williamson, & Müllensiefen, 2012; Müllensiefen, Jones, Jilka, Stewart, & Williamson, 2014). In general, it has been found that INMI is a fairly common, everyday experience and many different situational factors can trigger many different types of music to become INMI (Beaman & Williams, 2010; Halpern & Bartlett, 2011; Hyman et al., 2013; Liikkanen, 2012a; Williamson et al., 2012). However, the initial question posed in this article of why certain songs might get stuck in our heads over other songs is still not well understood. The reason this question is so difficult to answer may reside with the fact that the likelihood of a tune becoming INMI is potentially influenced by a wide array of both intramusical (e.g., musical features and lyrics of a song) and extramusical factors (e.g., radio play, context in which it appears as INMI, previous personal associations with a song, and the individual cognitive availability of a song). The present research examines some of these previously unaddressed factors by examining the musical features and popularity (e.g., chart position, recency of being featured in the charts) of songs frequently reported as INMI.

### Related Previous Research on INMI

Several researchers have examined extramusical features that increase the likelihood that a song will become INMI. Lab-based

Kelly Jakubowski, Department of Psychology, Goldsmiths, University of London; Sebastian Finkel, Department of Medical Psychology and Behavioral Neurobiology, University of Tübingen; Lauren Stewart, Department of Psychology, Goldsmiths, University of London, and Center for Music in the Brain, Department of Clinical Medicine, Aarhus University and The Royal Academy of Music Aarhus/Aalborg, Denmark; Daniel Müllensiefen, Department of Psychology, Goldsmiths, University of London.

This study was funded by a grant from the Leverhulme Trust, reference RPG-297, awarded to Lauren Stewart.

Correspondence concerning this article should be addressed to Kelly Jakubowski, who is now at Department of Music, Durham University, Palace Green, Durham DH1 3RL, United Kingdom. E-mail: kelly.jakubowski@durham.ac.uk



Kelly Jakubowski et al. · 2016 · Dissecting an Earworm

# What is a hook?

# What makes a hook?

Mixing?

Stereo balance?

Rhythm?

Harmony?

Melody?

Tempo?

Improvisation?

Sound effects?

Lyrics?

Studio editing?

Distortion?

Instrumentation?

Dynamics?

Gary Burns · 1987 · A Typology of 'Hooks' in Popular Records

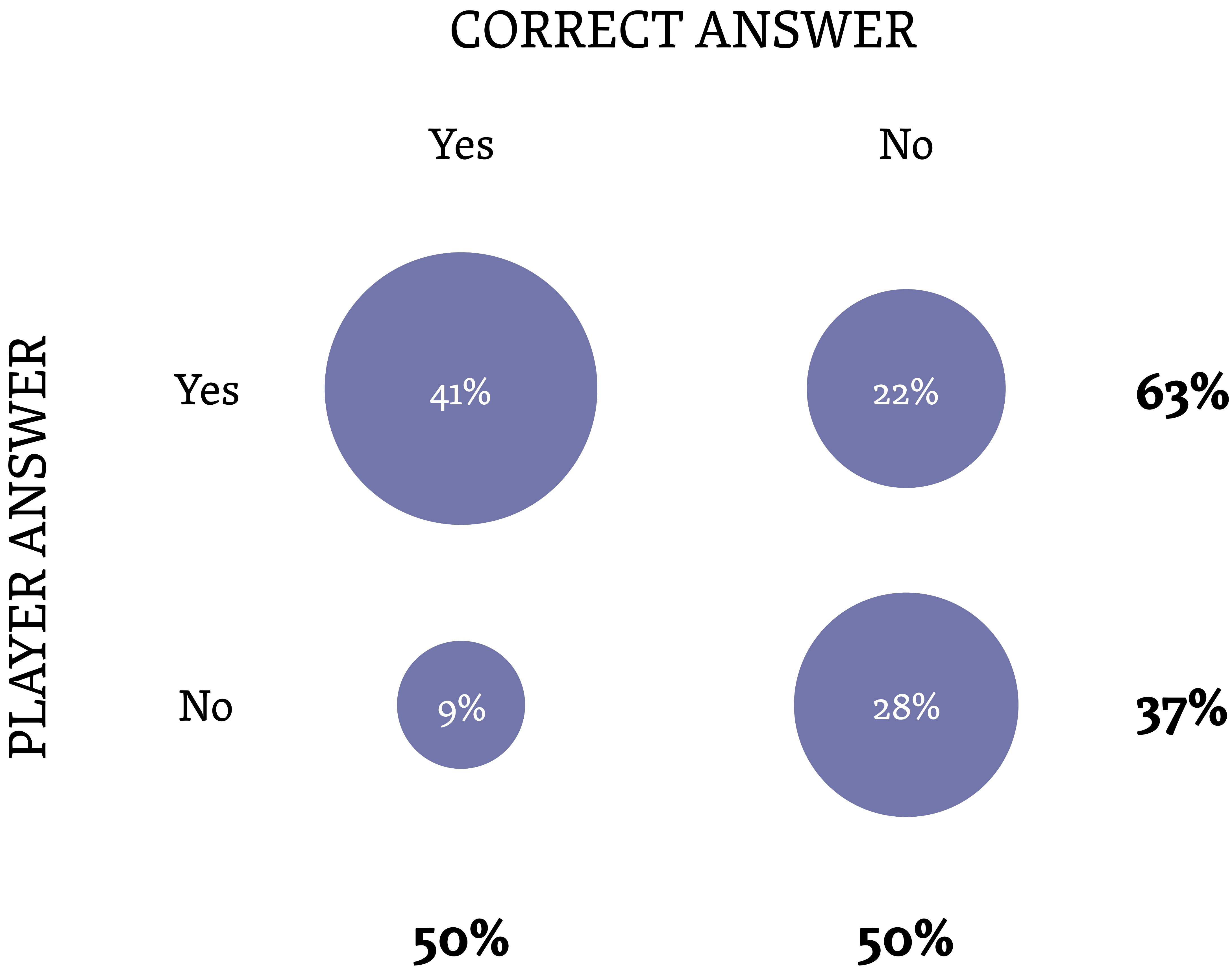

## Recognition

- Song and segment IDs
- Forced binary response
- Response time (< 15 s)

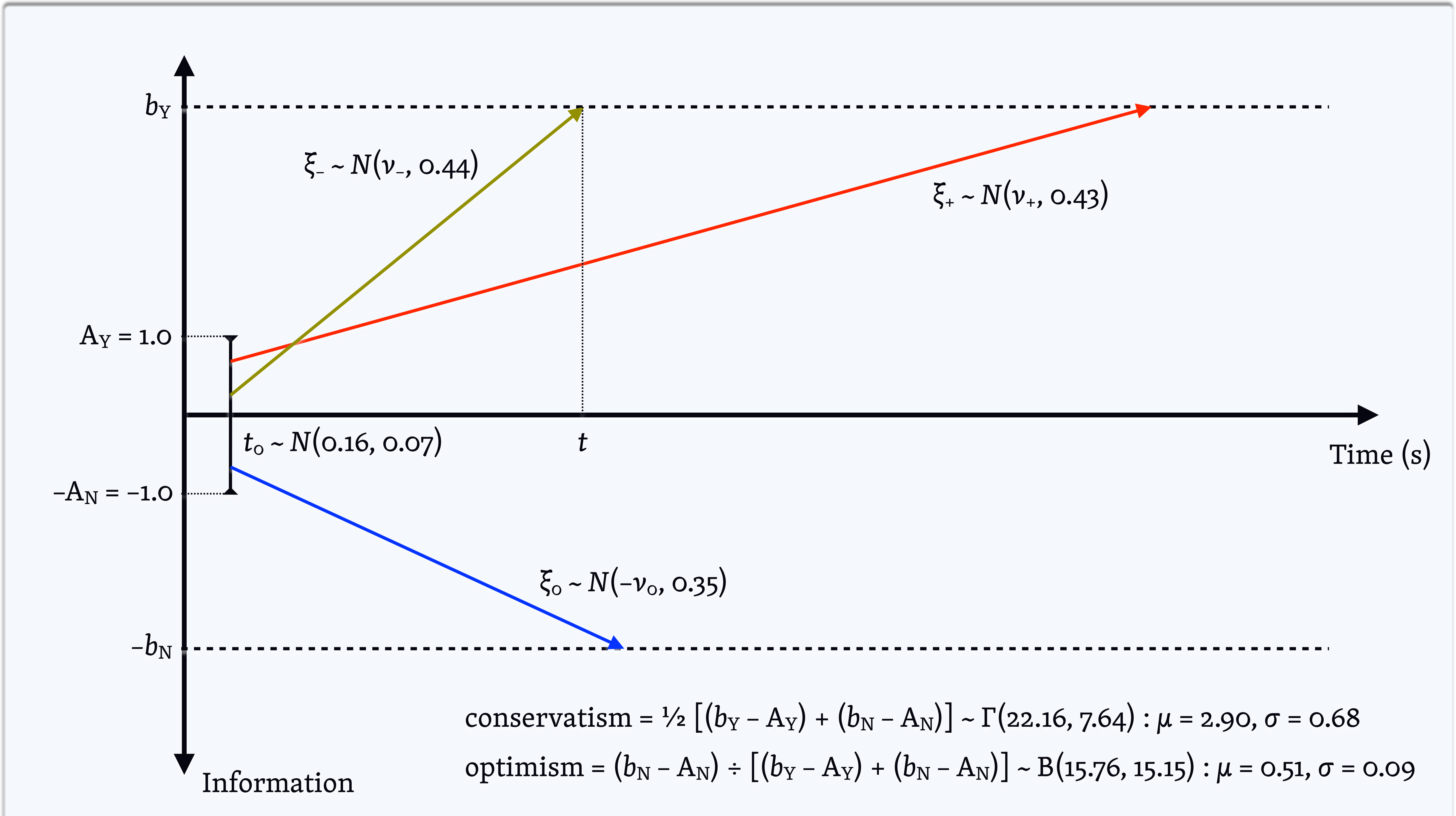

## Singalong


## Verification

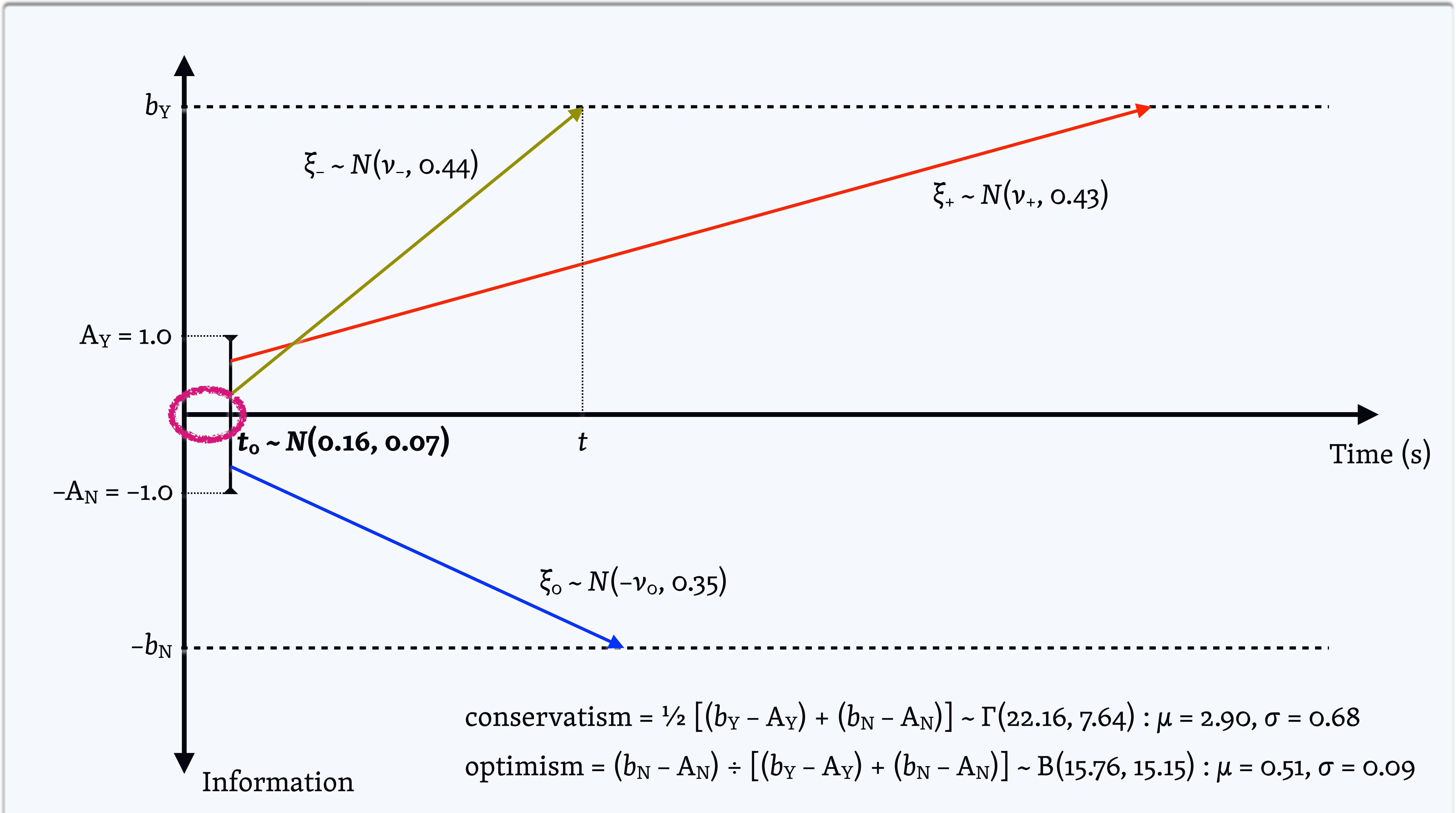
- Stimulus (correct/offset)
- Forced binary response
- Response time (unlimited)


CORRECT ANSWER
Yes
No
PLAYER ANSWER
Yes
41%
22%
63%
No
9%
28%
37%
50%
50%

# Measuring Catchiness




# Linear Ballistic Accumulators (Brown & Heathcote 2008)

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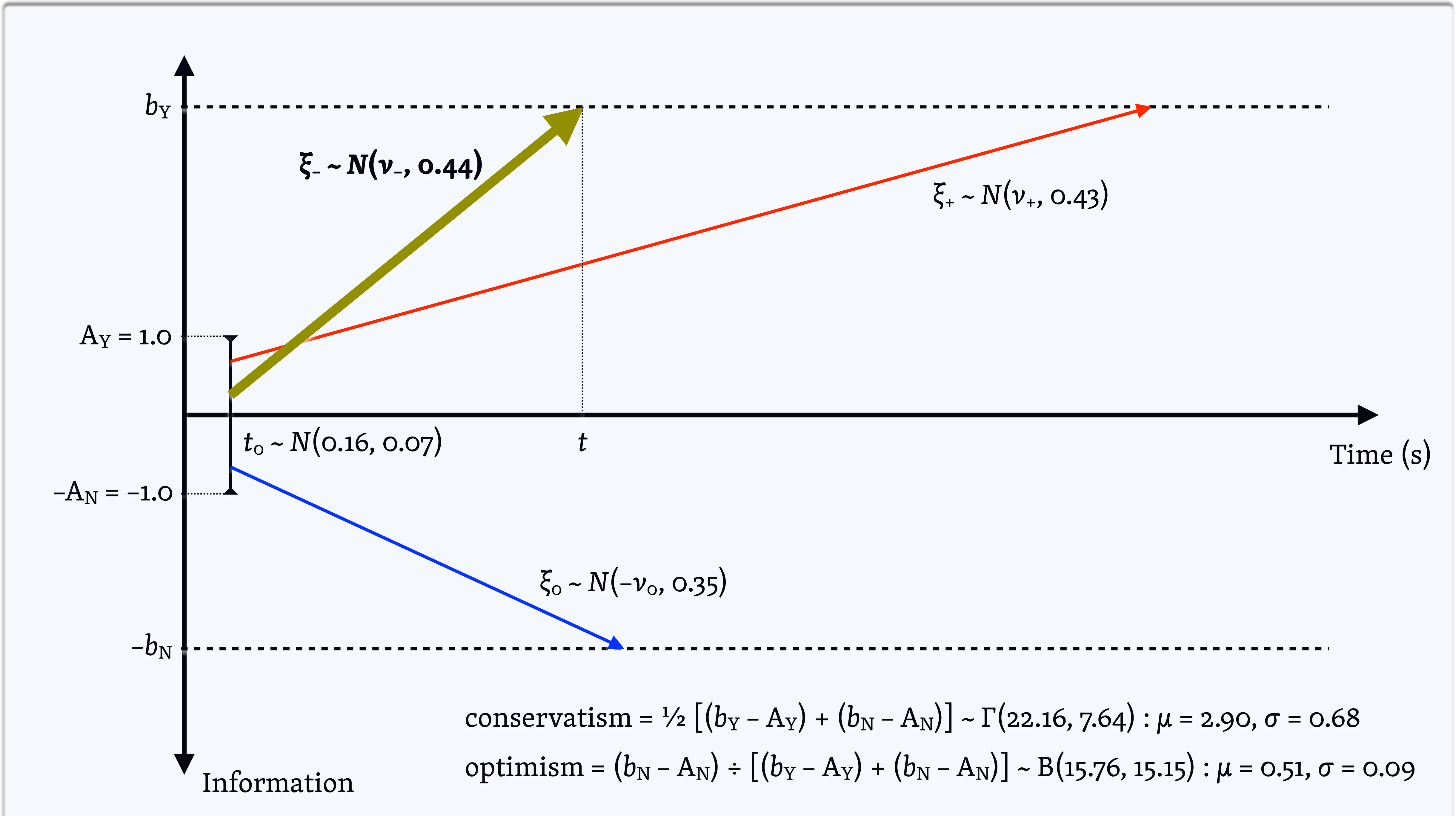


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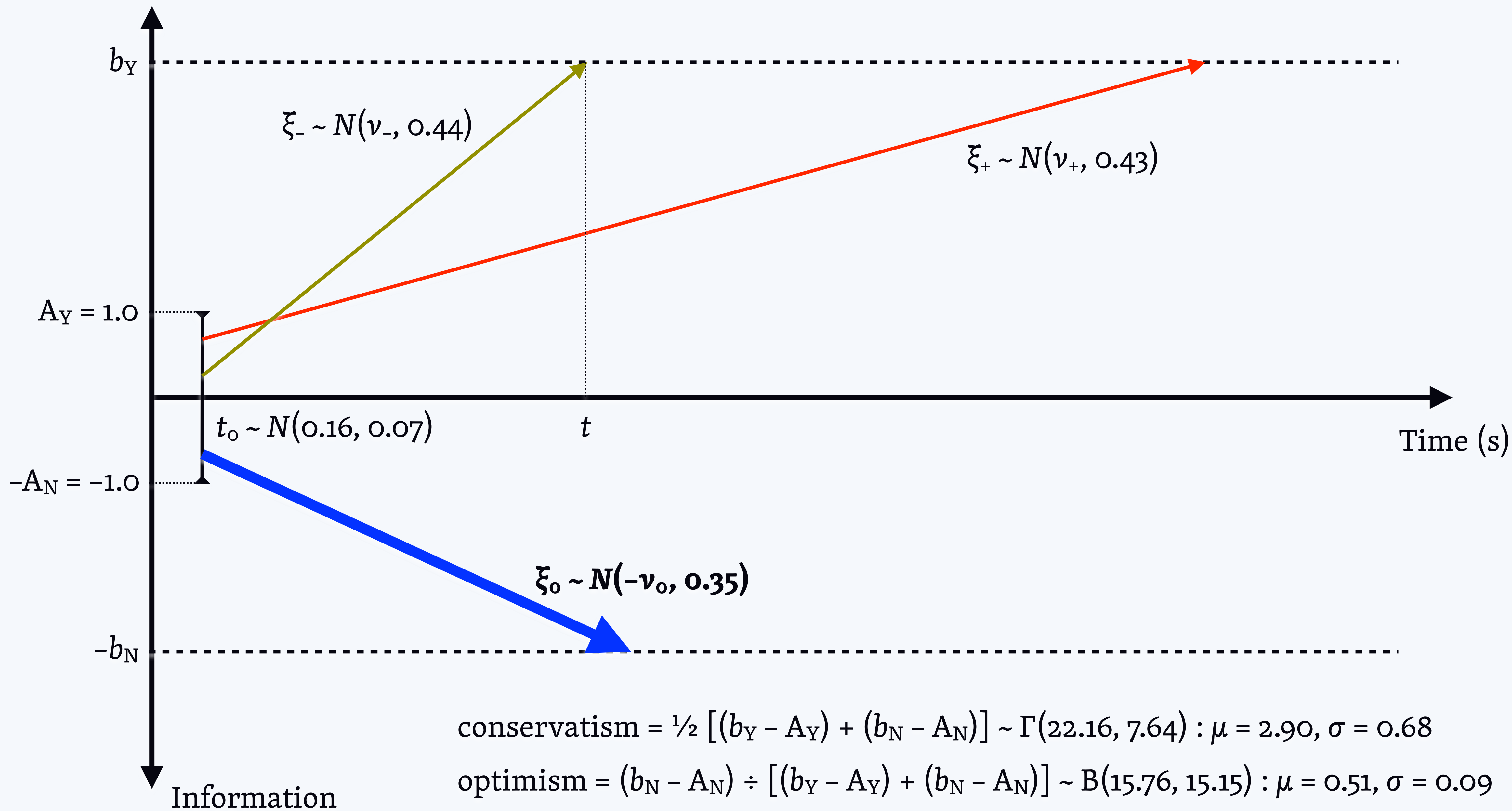


conservatism = ½ $[(b_Y - A_Y) + (b_N - A_N)] \sim \Gamma(22.16, 7.64) : \mu = 2.90, \sigma = 0.68$

optimism = $(b_N - A_N) \div [(b_Y - A_Y) + (b_N - A_N)] \sim B(15.76, 15.15) : \mu = 0.51, \sigma = 0.09$

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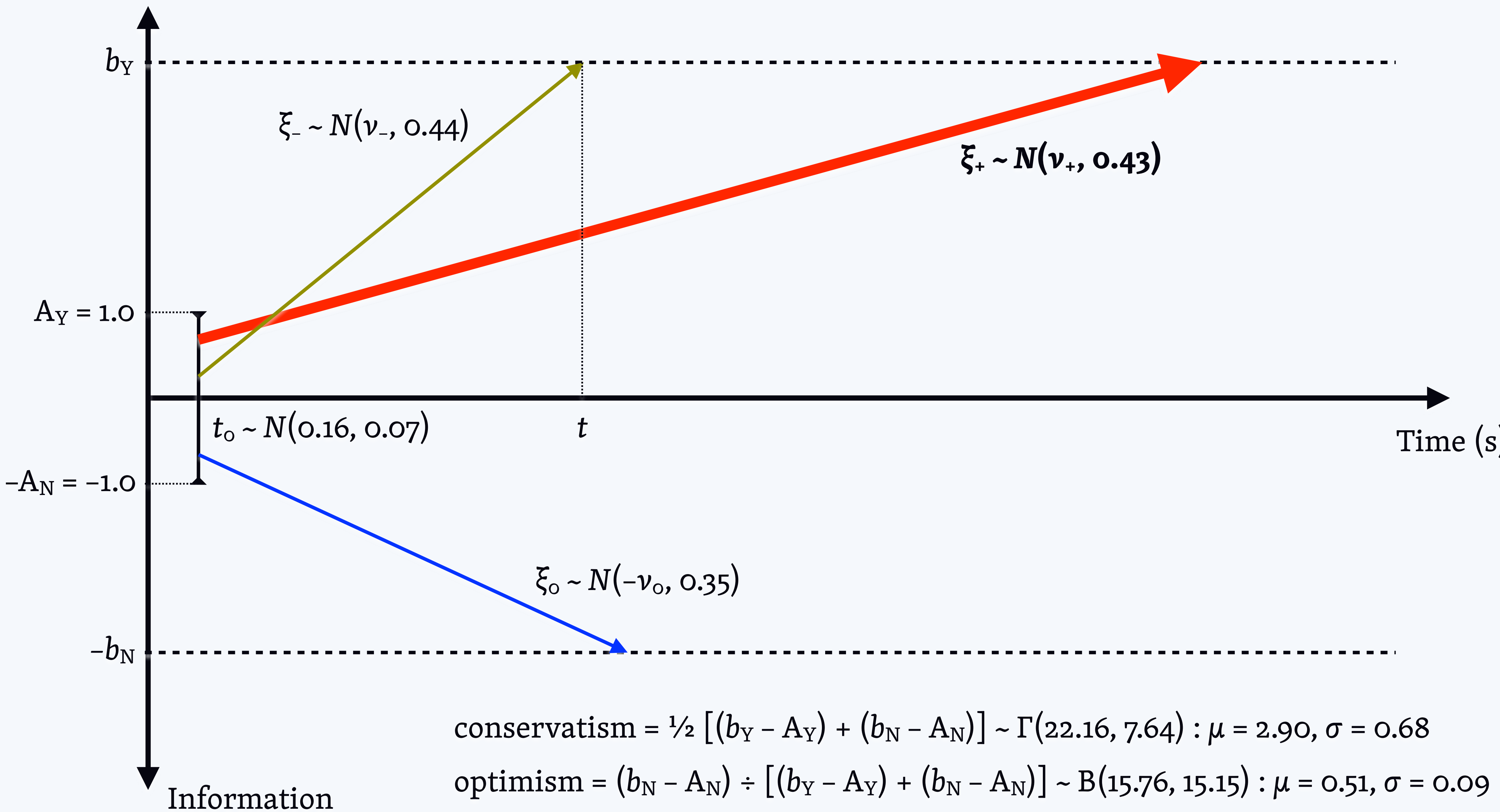


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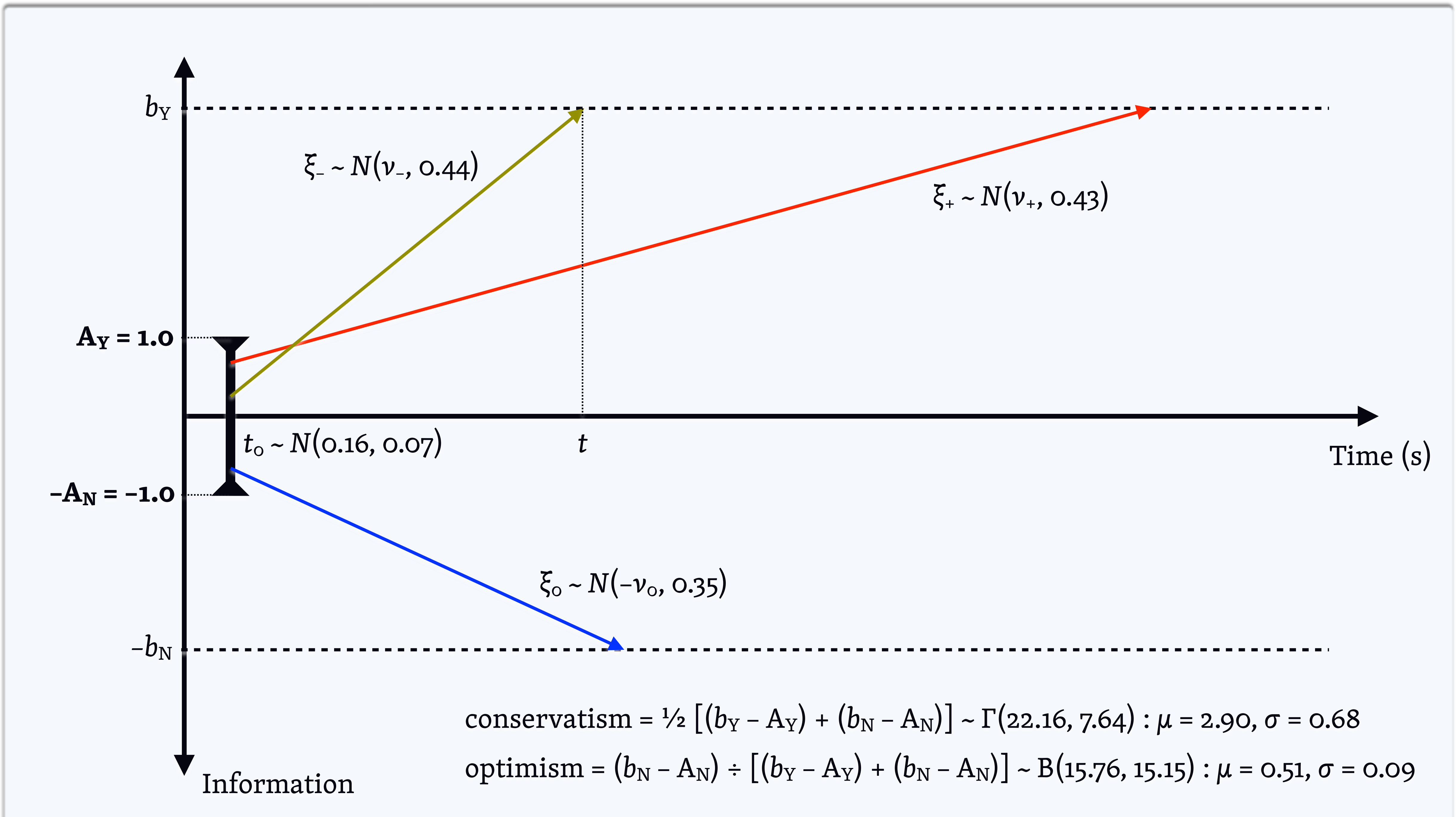


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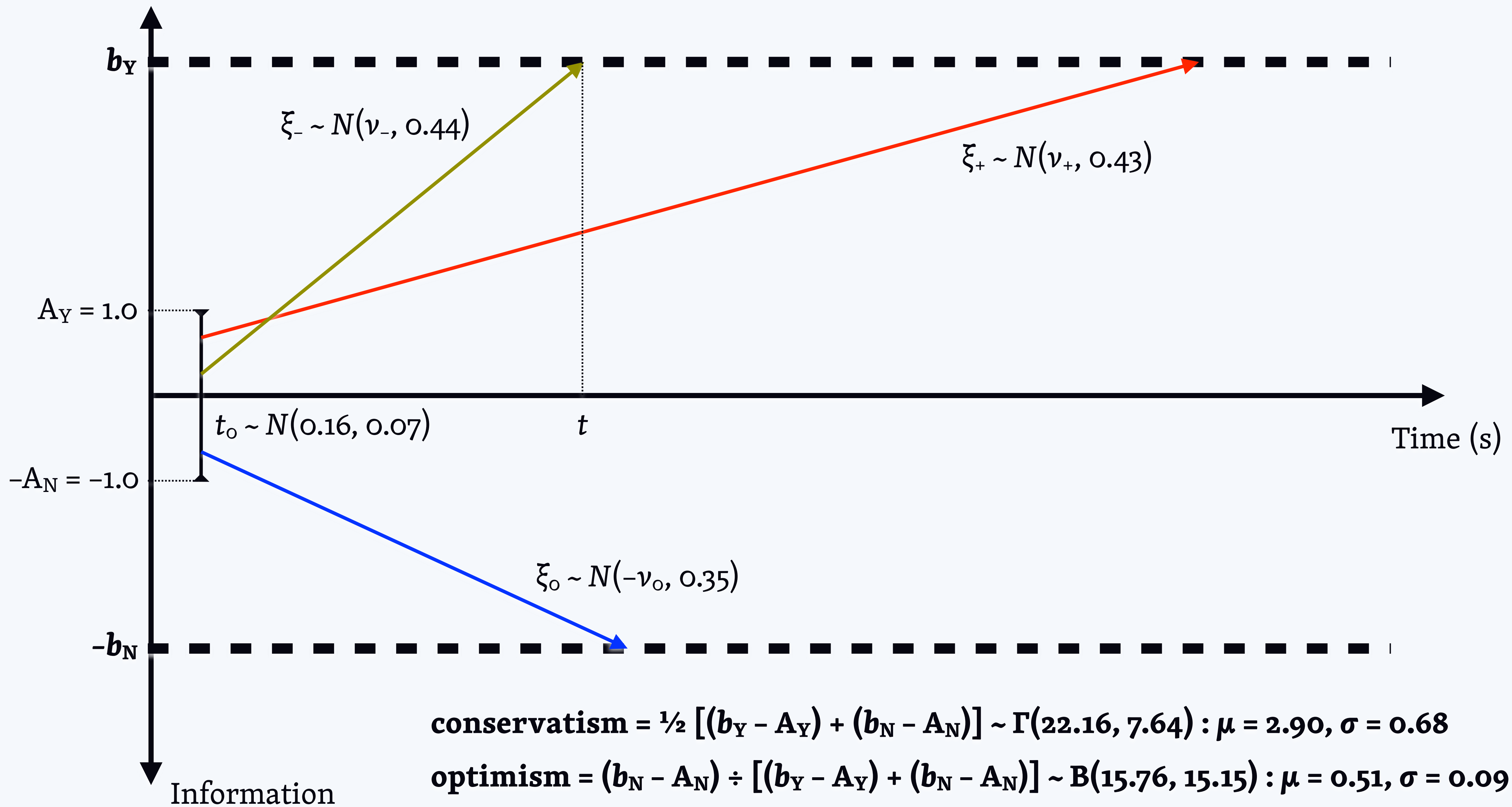


**conservatism** $= \frac{1}{2}\,[(b_Y - A_Y) + (b_N - A_N)] \sim \Gamma(22.16, 7.64) : \mu = 2.90, \sigma = 0.68$

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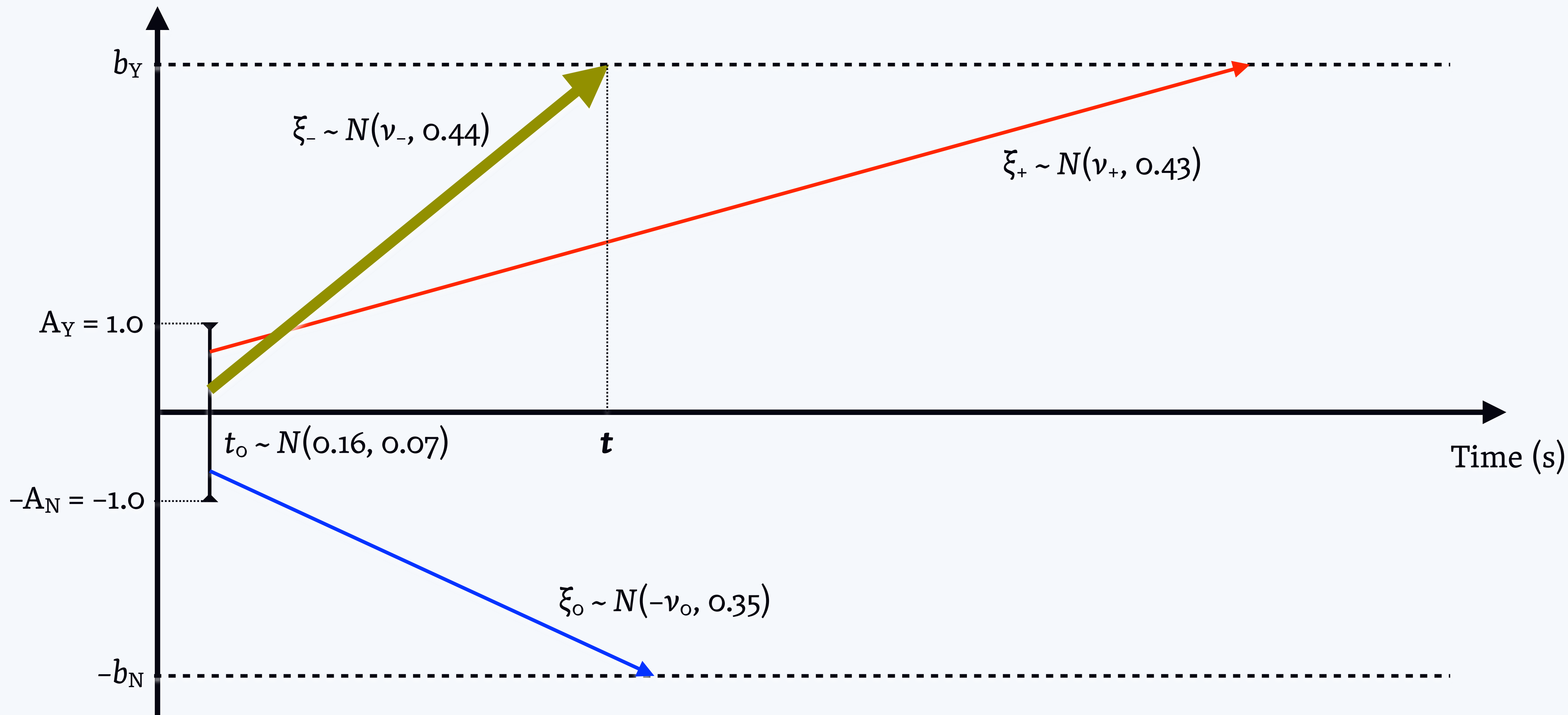


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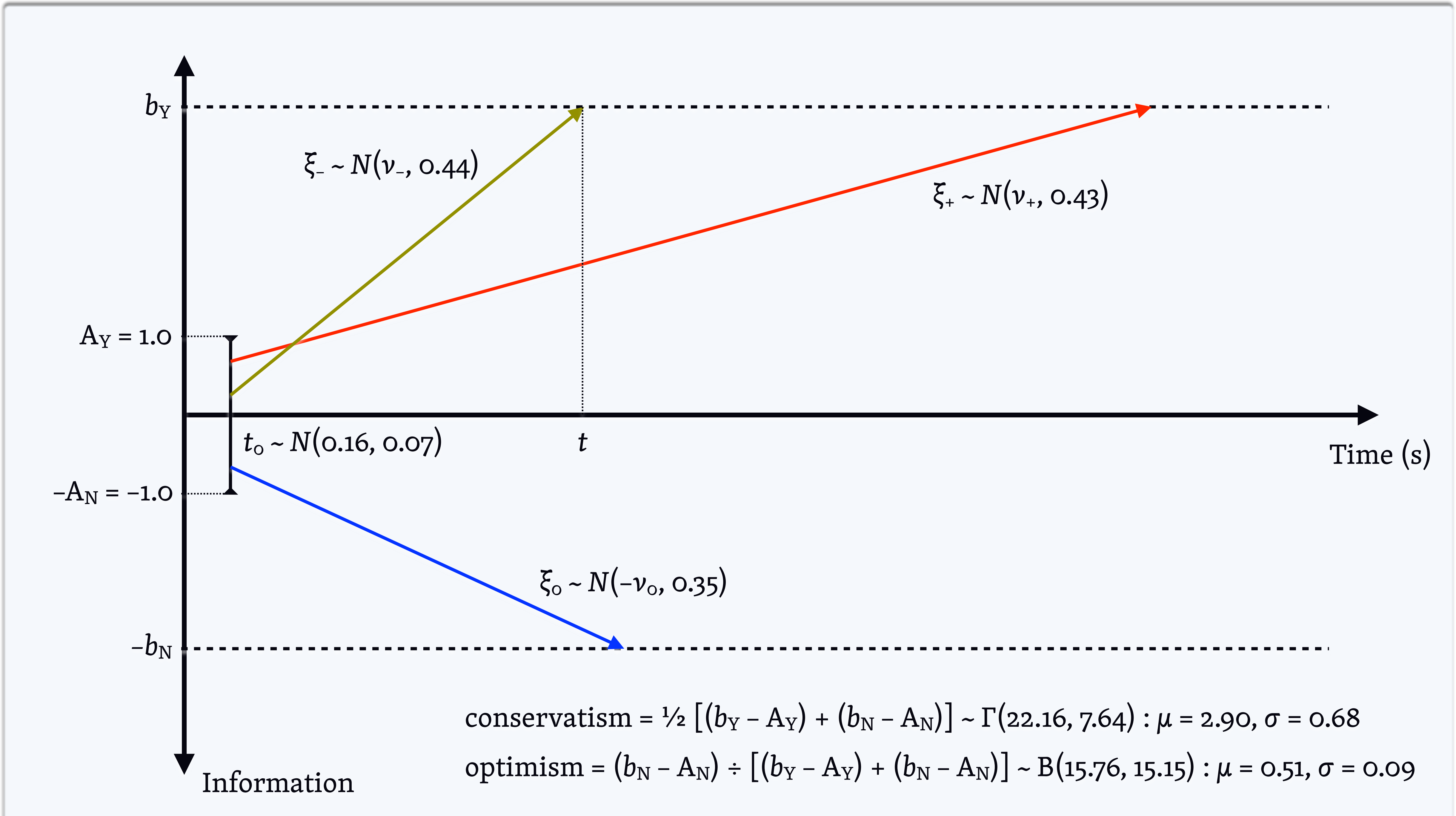


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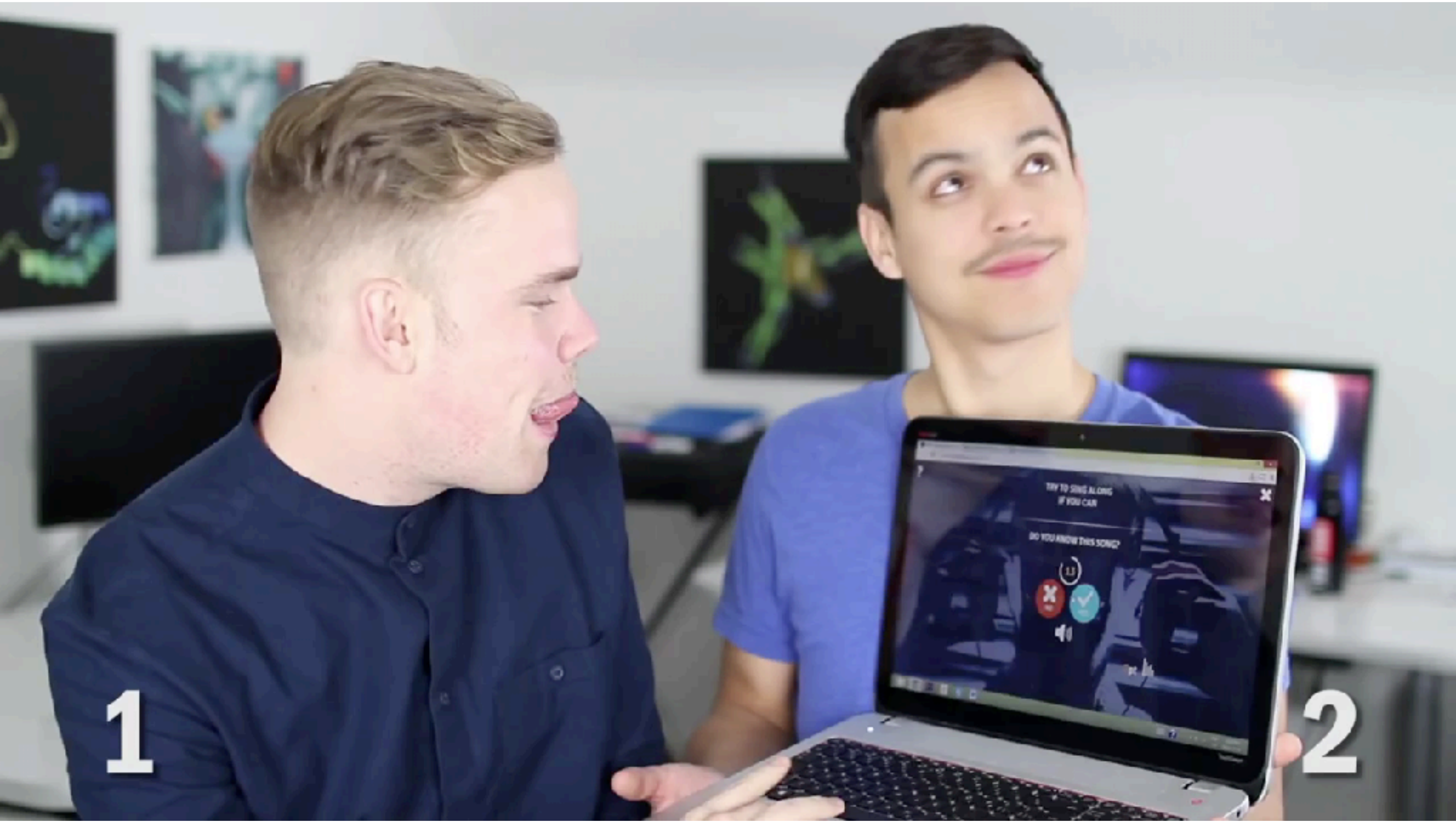
TRY TO SING ALONG
IF YOU CAN
DO YOU KNOW THIS SONG?
1
2


TMZ

# Top 10

| | Artist | Title | Year | Rec. Time (s) |
|---|---|---|---|---|
| 1 | Spice Girls | Wannabe | 1996 | 1.78 |
| 2 | Aretha Franklin | Think | 1968 | 1.85 |
| 3 | Queen | We Will Rock You | 1977 | 1.85 |
| 4 | Christina Aguilera | Beautiful | 2002 | 2.00 |
| 5 | Amy MacDonald | This Is the Life | 2007 | 2.01 |
| 6 | The Police | Message in a Bottle | 1979 | 2.08 |
| 7 | Bon Jovi | It's My Life | 2000 | 2.16 |
| 8 | Bee Gees | Stayin' Alive | 1977 | 2.16 |
| 9 | ABBA | Dancing Queen | 1976 | 2.17 |
| 10 | 4 Non Blondes | What's Up | 1993 | 2.20 |

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| 5 | Amy MacDonald | This Is the Life | 2007 | 2.01 |
| 6 | The Police | Message in a Bottle | 1979 | 2.08 |
| 7 | Bon Jovi | It's My Life | 2000 | 2.16 |
| 8 | Bee Gees | Stayin' Alive | 1977 | 2.16 |
| 9 | ABBA | Dancing Queen | 1976 | 2.17 |
| **10** | **4 Non Blondes** | **What's Up** | **1993** | **2.20** |

# Top 10

| | Artist | Title | Year | Rec. Time (s) |
|---|---|---|---|---|
| 1 | Spice Girls | Wannabe | 1996 | 1.78 |
| 2 | Aretha Franklin | Think | 1968 | 1.85 |
| 3 | Queen | We Will Rock You | 1977 | 1.85 |
| 4 | Christina Aguilera | Beautiful | 2002 | 2.00 |
| 5 | Amy MacDonald | This Is the Life | 2007 | 2.01 |
| 6 | The Police | Message in a Bottle | 1979 | 2.08 |
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# Break

# Predicting Hooks


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# Hook Predictors

| Factor | % Drift-Rate Increase | 99.5% CI |
|---|---|---|
| Melodic Repetition | 12.0 | [5.4, 19.0] |
| Vocal Prominence | 8.0 | [0.8, 15.8] |
| Melodic Conventionality | 7.8 | [1.3, 14.7] |
| Melodic Range Conventionality | 6.8 | [0.9, 13.0] |

$R^2_{\text{marginal}} = .10$ $R^2_{\text{conditional}} = .47$

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# Model: Audio Features

| Feature | Coefficient | 95% CI |
|---|---|---|
| **Vocal Prominence** | **0.14** | [0.10, 0.18] |
| **Timbral Conventionality** | **0.09** | [0.05, 0.13] |
| **Melodic Conventionality** | **0.06** | [0.02, 0.11] |
| **M/H Entropy Conventionality** | **0.06** | [0.02, 0.10] |
| **Sharpness Conventionality** | **0.05** | [0.02, 0.09] |
| **Harmonic Conventionality** | **0.05** | [0.01, 0.10] |
| **Timbral Recurrence** | **0.05** | [0.02, 0.08] |
| **Mel. Range Conventionality** | **0.05** | [0.01, 0.08] |

$R^2_{\text{marginal}} = .10$ $R^2_{\text{conditional}} = .47$

# Predictions: Eurovision 2016

| Country | Score | Vocal | Tim. | Mel. | MHE | Sharp. | Harm. | TR | Range |
|---|---|---|---|---|---|---|---|---|---|
| 1 ESP | **10.0** | 3.1 | −0.2 | −0.7 | 1.1 | 0.2 | −0.7 | 0.2 | **1.6** |
| 2 GBR | **10.0** | **3.4** | **1.4** | 0.1 | 1.0 | −0.5 | 0.1 | **−1.8** | 0.3 |
| 3 SWE | **9.8** | 1.8 | 0.9 | −0.3 | 0.4 | −0.3 | −0.3 | 1.0 | 0.3 |
| 4 LTU | **9.8** | 2.7 | 0.4 | 0.3 | 0.5 | 0.4 | 0.3 | 0.2 | −0.1 |
| 5 DEU | **9.6** | 3.4 | 0.4 | 0.3 | −0.1 | 0.0 | 0.3 | 0.2 | 0.1 |
| 6 AUS | **9.5** | 1.4 | −0.1 | **−1.3** | **2.6** | 1.3 | −1.3 | 0.8 | 0.5 |
| 7 AUT | **9.5** | 2.7 | 1.1 | 0.8 | −0.6 | −0.3 | 0.8 | 0.3 | −0.4 |
| 8 FIN | **9.4** | 2.3 | 0.4 | −1.8 | 0.4 | 0.2 | **−1.8** | 0.1 | 1.1 |
| 9 CHE | **9.4** | 2.4 | 0.7 | 0.9 | 1.1 | −0.2 | 0.9 | 0.8 | −1.2 |
| 10 AZE | **9.3** | 2.9 | 0.5 | 0.3 | 1.1 | −0.2 | 0.3 | 0.4 | 0.1 |
| 12 NLD | **9.1** | 1.5 | 0.4 | 0.6 | 1.2 | −0.4 | 0.6 | −0.7 | 0.7 |
| 39 HUN | **7.5** | 1.6 | 0.7 | −0.1 | 0.9 | −0.3 | −0.1 | −0.9 | −0.4 |
| 40 MNE | **7.1** | 0.6 | 0.0 | −0.8 | 0.3 | **2.5** | −0.8 | 0.4 | −0.7 |
| 41 ISL | **6.9** | 0.6 | −0.6 | −0.7 | 1.7 | −0.5 | −0.7 | 0.6 | −0.4 |
| 42 GEO | **6.8** | 0.3 | 1.2 | −0.3 | 0.0 | −0.1 | −0.3 | 0.0 | **−1.6** |
| 43 ARM | **6.5** | 0.0 | −0.5 | 0.4 | 0.2 | 0.4 | 0.4 | 0.5 | 1.5 |

# Model: Symbolic Features

| Feature | Coefficient | 95% CI |
|---|---|---|
| **Melodic Repetitivity** | **0.12** | [0.06, 0.19] |
| **Melodic Conventionality** | **0.07** | [0.01, 0.13] |

$R^2_{\text{marginal}} = .07$ $R^2_{\text{conditional}} = .47$

# Predictions: *Nederlandse Liederenbank*

| Melody | | Score | Repetitivity | Conventionality |
|---|---|---|---|---|
| 1 | NLB152784_01 | **10.0** | 7.1 | −0.1 |
| 2 | NLB075307_03 | **9.8** | 7.2 | −0.5 |
| 3 | NLB073393_01 | **8.7** | 6.2 | −0.5 |
| 4 | NLB070078_01 | **8.0** | 5.4 | −0.2 |
| 5 | NLB076495_01 | **7.6** | 5.6 | −1.2 |
| 6 | NLB075158_01 | **7.5** | 4.8 | −0.3 |
| 7 | NLB072500_01 | **7.2** | 4.5 | −0.2 |
| 8 | NLB070535_01 | **7.2** | 4.5 | −0.3 |
| 9 | NLB073939_01 | **7.1** | 4.4 | −0.3 |
| 10 | NLB073269_02 | **7.1** | 4.2 | 0.0 |
| 180 | NLB075325_02 | **4.8** | 1.1 | −0.1 |
| 356 | NLB074182_01 | **3.7** | −0.8 | −0.4 |
| 357 | NLB073822_01 | **3.6** | −0.7 | −0.9 |
| 358 | NLB072154_01 | **3.6** | −1.0 | −0.3 |
| 359 | NLB071957_03 | **3.6** | −1.0 | −0.5 |
| 360 | NLB074603_01 | **3.5** | −1.6 | 0.0 |

Pubquizteam

# A Diva Lover

| Factor | b | SE |
|---|---|---|
| Intensity | −0.26 | 0.07 |
| Recurrence | 0.15 | 0.07 |
| Tonal Conventionality | −0.15 | 0.06 |

# Age Balance

| Factor | b | SE |
|---|---|---|
| Rhythmic Irregularity | 0.30 | 0.09 |
| Rhythmic Conventionality | 0.20 | 0.08 |
| Event Sparsity | 0.19 | 0.08 |

# Hip-Hop Fanatic

| Factor | b | SE |
|---|---|---|
| Melodic Complexity | −0.21 | 0.06 |
| Rhythmic Conventionality | −0.13 | 0.06 |
| Harmonic Complexity | −0.11 | 0.05 |

# Ketchup?

| Factor | b | SE |
|---|---|---|
| Intensity | −0.25 | 0.22 |
| Recurrence | −0.21 | 0.19 |

# Summary

# Summary

- **Long-term musical salience**
    - What are the musical characteristics we carry into old age?
- **How do we measure it?**
    - *Drift rates*, or rates of information accumulation in the brain.

# Summary

- **What is a hook?**
  - Seems to be quite literally a ‘catchy tune’.
- **How do listeners differ?**
  - Divas, generations, genres…
  - …and ketchup?

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